

How (Not) to Identify Demand Elasticities in Dynamic Asset Markets

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August 20, 2025

Abstract

We evaluate approaches to estimating demand elasticities in dynamic asset markets, both theoretically and empirically. We establish strict, necessary conditions that the dynamics of instrumented asset price variation must satisfy for valid identification. We illustrate these insights in a general equilibrium model of dynamic trade and derive the magnitude of biases that arise when these conditions are violated. Estimates based on static IO models are severely biased when the instrumented price variation is persistent or predictable. Empirically, we show that commonly used instruments yield elasticity estimates that are off by orders of magnitude, or even have the wrong sign. In contrast to standard multiplier calculations, our theory characterizes the dynamic asset market interventions required to sustain a given price path support process, with direct implications for policies such as Quantitative Easing (QE).

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1 Introduction

A longstanding literature in finance, beginning with [Shleifer \(1986\)](#) and [Harris and Gurel \(1986\)](#), has examined whether demand curves for financial assets are downward sloping and whether the time horizon of measurement matters. More recent contributions have applied tools from the structural industrial organization (IO) literature to estimate institutional demand for long-lived securities, concluding that asset markets are inelastic (e.g., [Kojen and Yogo \(2019\)](#), hereafter KY19).

In this paper, we assess the identification strategies underlying these estimates when agents can trade assets dynamically. We find that instruments used in the existing literature applying static IO demand models introduce large and systematic biases. These biases stem from the following conceptual tension. In a standard IO setting with static product characteristics, a price elasticity measures how demand responds to a marginal price change, holding the product’s intrinsic features constant. In contrast, in asset markets, a central characteristic of a security is the stochastic stream of future cash flows it delivers to the investor. In particular, since an investor can sell securities to others at future points in time, the path of future trading prices $\{P_\tau\}_{\tau>t}$ is itself an intrinsic characteristic. Any candidate instrument that shifts the contemporaneous price at time t while also affecting future resale values thus violates the exclusion restriction. In particular, if price shifts exhibit momentum or persistence, the resulting estimates can no longer be interpreted as price elasticities. These concerns are not merely theoretical: in practice, financial institutions actively engage in dynamic trading strategies. Yet such strategic trading dynamics are absent in static IO models.

Our contribution is both theoretical and empirical. On the theory side, we develop a general equilibrium model of dynamic trade to identify necessary conditions for valid elasticity identification using either time-series or cross-sectional holdings data. Specifically, we show that price variation induced by valid instruments must generally (i) affect prices for at most one trading period, and (ii) be unanticipated *ex ante*. These conditions ensure that the instrument does not itself introduce or alter state variables in traders’ dynamic optimization problems. While the absence of anticipation is particularly critical for time-series identification (e.g., using index reconstitution event studies),¹ full resolution of price shifts within a single trading

¹When price changes induced by index inclusion effects are either anticipated or resolve over

period is necessary for both time-series and cross-sectional approaches.

Using our model, we derive simple formulas that quantify the biases in elasticity estimates when these conditions are violated. In particular, we obtain such formulas for two stylized types of price dynamics: (1) gradual resolution of price shifts, and (2) predictable price build-up, as in the case of momentum (see [Binsbergen et al., 2023](#)). For the resolution case, we show that the bias in the estimated elasticity is proportional to the probability that a price shift resolves within an agent’s portfolio adjustment interval. For example, if institutions can rebalance daily and a price shift resolves with a constant per-period probability corresponding to an expected duration of two years, the elasticity estimate has a magnitude of only 1/730th of the true elasticity. In the momentum case, the bias is even more severe: the estimated elasticity takes the opposite sign of the true elasticity. The intuition is straightforward. When variation inducing a positive price shift also predicts higher future returns, agents rationally tilt *toward* the security, creating the false appearance of a negative elasticity.

While our bias corrections apply under stylized dynamics for price path shifts — such as constant per-period resolution or build-up probabilities — we emphasize that no general adjustment factor can correct the distortions inherent in static cross-sectional identification and event-study time-series approaches.

A simple example illustrates this central point. Suppose the Federal Reserve unexpectedly and credibly announces that it will do “whatever it takes” to raise the price of an asset by 1% for one year, relative to the counterfactual price path without intervention. After one year, the program is permanently discontinued. To streamline the argument, assume the asset pays no dividends during that year and that investors have log utility.

How does this exogenous increase in prices affect investors’ optimal portfolio weights? The answer is: not at all. Once the surprise announcement is made and the price has shifted upwards, the *return* distribution going forward is unaffected by the intervention until the program ends in one year. As a result, both static cross-

longer horizons, the resulting elasticity estimates are generally biased. Early studies, such as [Harris and Gurel \(1986\)](#), documented mean reversion within two weeks, but more recent work suggests that the index inclusion effect has either disappeared for the S&P 500 index ([Greenwood and Sammon, 2025](#)) or exhibits longer-lasting effects for other indices. See [Chang et al. \(2015\)](#); [Beneish and Whaley \(1996\)](#); [Lynch and Mendenhall \(1997\)](#); [Wurgler and Zhuravskaya \(2002\)](#).

sectional and event-study-based approaches using data on portfolio weights around the time of the event yield elasticity estimates of zero.

But does this imply that asset markets are inelastic? Our answer is: not at all. The crux is that the shock upon impact alters the asset's intrinsic characteristics, that is, its future resale values — it does not speak to how elastic investors are. To see why, note that investors will strongly tilt their portfolio away from the asset in the final trading period before the one-year mark, when the price is expected to fall by 1%. For the program not to unravel by backward induction, the Federal Reserve must therefore purchase large quantities of the asset at that time—reflecting log investors' true, highly elastic behavior. Rational investors will dump the asset in the last trading period before the program ends, anticipating that an abnormal price drop is imminent.²

This example illustrates that in dynamic trading environments, variation in holdings observed around the time of an exogenous price shift may provide no meaningful information about either the true demand elasticity or the quantity the Federal Reserve must purchase. In this case, both static, cross-sectional identification and event-study time-series identification fail.

Note also that the conditions for identification we characterize cannot be relaxed simply by the econometrician choosing a lower data sampling frequency, as this frequency is distinct from the one at which agents can adjust their portfolios. Contemporaneous variation in portfolio weights reflects return opportunities over the next trading period, not over the interval until the econometrician next observes or samples holdings. In the above example, investors' portfolio shares are constant throughout the whole year and only briefly shift in the last trading period before reverting back to their original level.³

²A closely related policy intervention is a forward commitment by the Federal Reserve to undertake any purchases necessary, one year from now, to lift the asset's price by 1% for a single trading period, *relative to the case of no intervention*. By backward induction, prices will already rise at the time of the announcement, as agents anticipate being able to resell the asset at a 1% higher price at the end of the year. By construction, this intervention involves no trade between the Federal Reserve and other market participants at the time of the announcement. As a result, the incorrectly inferred unit price elasticity of demand is zero.

³Similarly, our points about elasticity identification are not resolved by appealing to the notion of long-run elasticities. In standard product markets, a long-run elasticity considers a longer time horizon over which consumers are able to adjust—for example, by switching to alternative products. This typically leads to *more* elastic responses. Moreover, whereas a regular good can plausibly maintain its intrinsic characteristics in the face of persistent price changes, this is infeasible for financial assets

Our empirical results are closely connected to these issues. In particular, we find that cross-sectional variation in KY19’s instrumented price variable, $\widehat{me}$ (instrumented market equity), does not satisfy the conditions required for valid elasticity identification in dynamic trading environments. In fact, cross-sectionally, higher values of $\widehat{me}$ are either unrelated—or even positively related—to average returns over the following month. Rational investors, therefore, should not tilt away from high- $\widehat{me}$ stocks but, if anything, overweight them. According to our model, using such variation as an instrument mechanically yields elasticity estimates that are close to zero or even negative—the opposite sign of the true price elasticity.

Consistent with this prediction, we find that across institutions and assets, roughly half of the price elasticity estimates in the KY19 framework turn out negative when the estimation is not constrained to produce positive values.⁴ These results underscore that even when true demand elasticities are large (in excess of 1,000) using instruments that induce persistent or momentum-type dynamics in price shifts mechanically yields estimated price elasticities close to zero, or even negative.

Our results also emphasize that the concept of exogeneity typically invoked in economic models is insufficient for the proper identification of demand elasticities in financial markets. Even if a shock that shifts prices would be regarded as truly exogenous within the context of a model (e.g., if induced by a supply shock randomly chosen by nature), it still cannot be used to identify demand elasticities if it alters the intrinsic characteristics of the asset. However, an exogenous shock that affects prices across multiple trading dates induces exactly such a change. As a result, it introduces or alters dynamic state variables in traders’ optimization problems, causing elasticity estimates to reflect changes in these state variables rather than the contemporaneous price.

Our analysis of asset demand in a dynamic general equilibrium setting yields sharp predictions regarding the effectiveness of dynamic asset purchase programs and other supply-affecting policies. First, we show that the persistence of a policy’s intended price path support has a dramatic impact on the size of the *initial* supply intervention required to achieve it. For instance, under a constant per-period resolution probability, increasing the expected duration of a 1% price shift from one week

that agents can trade dynamically.

⁴Specifically, this occurs when we relax KY19’s assumption that the estimated beta on instrumented market equity in the demand equation is bounded above by one.

to one year reduces the required residual supply shock at inception by 98%. This reflects the fact that rational, optimizing traders lean far more aggressively against a price shift when it is expected to reverse quickly. The results also differ markedly depending on whether policy commitments have a fixed expiration date—as in our introductory example—or resolve randomly.

Second, we characterize the path of dynamic asset market interventions required to sustain a given price path support process. This analysis reveals significant limitations of the typical multiplier calculations considered in the literature. Even in the case of a single risky asset and a safe asset, there is no single multiplier that characterizes the relationship between purchase quantities and the resulting price path response. In particular, purchase programs that solely promise future interventions naturally generate infinite announcement multipliers, mirroring the inverse of an erroneously inferred zero price elasticity. Overall, our findings have useful implications for the literature on quantitative easing and the dynamics of policy interventions (see, e.g., [Haddad et al., 2025a](#)).

Our insights challenge how elasticity estimates are commonly interpreted in the existing literature. [Davis et al. \(2025\)](#), for example, argue that limited price pass-through and the presence of unspanned factors imply that price elasticities are expected to be low, on the order of 5. In contrast, we show that in dynamic trading environments, estimates based on persistent or predictable price shocks capture agents' responsiveness to changes in asset characteristics rather than to purely contemporaneous price changes. As a result, such estimates cannot be interpreted as price elasticities. [He et al. \(2025\)](#) also examine asset demand in a dynamic general equilibrium setting, but explore agents' optimal quantity response to changes in expected returns, not prices. In contrast, our paper is concerned with price elasticities. This distinction is central in our analysis of the implications of the temporal disconnect between price level shifts and return opportunities and for our derivations of necessary conditions for instrument validity in the estimation of price elasticities. [He et al. \(2025\)](#) show that observed demand slopes with respect to expected returns can differ from true underlying slopes because exogenous supply shifts affect endogenous risk—specifically, return volatility and covariance—and alter the comovement of returns with future investment opportunities.

[Gabaix and Koijen \(2023\)](#) examine multipliers both empirically and theoretically.

They explain the large magnitudes of empirically estimated multipliers, particularly for the stock market, within a dynamic general equilibrium framework by introducing two frictions in capital allocation through institutions: fixed-share mandates and inertia. Moreover, [Gabaix and Koijen \(2023\)](#) show that persistence in flows leads to higher multiplier estimates and define a “market multiplier” as the multiplier associated with a fully persistent inflow. The authors state that rational models predict that this market multiplier is around $1/20$, whereas empirical estimates in the literature, as well as those obtained using their approach, yield values between 1.5 and 5.

Our paper contributes to this literature on multipliers by establishing several key results. First, multipliers used to measure price impact at the inception of multi-period purchases are insufficient and often misleading in characterizing the relationship between quantities and prices. This is because initial price movements are driven primarily by expectations about the future path of holdings rather than by the initial purchases themselves. In contrast, we characterize the entire path of incremental holdings required to sustain a given path of price shifts. Second, we show that permanent interventions can plausibly exhibit market multipliers of around 2 or higher without requiring additional frictions. Third, empirical estimates of multipliers should be expected to take high values (up to infinity) in practically relevant settings involving position build-up, such as central bank asset purchase programs. Importantly, such evidence on multipliers is fully consistent with market participants exhibiting very high price elasticities of demand.

Finally, our analysis is distinct from the important ongoing debate about the empirical validity of different substitution structures assumed in static models (e.g., [Fuchs et al. \(2025\)](#); [Haddad et al. \(2025b\)](#); [Koijen and Yogo \(2025\)](#)). While these papers highlight limitations of cross-sectional model structure, our contribution is to isolate dynamic violations of identification assumptions. By abstracting from spillovers and complementarities, we provide clean and tractable measures of how intertemporal dynamics distort elasticity estimates even in otherwise well-specified static demand models.

2 Model

We consider a continuous-time environment with two groups of agents — an investor group explicitly maximizing CRRA utility and an “outside group” introducing exogenous residual supply shocks. The latter group can be interpreted as noise traders or corporations engaging in state-contingent share issuances or repurchases. We start by detailing CRRA investors’ trading and consumption opportunities conditional on postulated equilibrium asset price dynamics. Thereafter, we characterize the outside group’s residual supply dynamics. We intentionally reverse engineer supply shocks to obtain a minimally complex state space and a clean characterization of the dynamics of shocks that can identify demand elasticities.

Preferences. There is a measure one of CRRA investors whose utility from consumption is given by

$$u(C) = \frac{C^{1-\gamma}}{1-\gamma}, \quad (1)$$

where $\gamma > 0$ is the coefficient of relative risk aversion. The subjective discount rate applied to future utility is denoted by ρ .

Assets. Agents can invest in multiple risky assets $j = 1, \dots, J$ and in a risk-free asset with return r_f . We postulate that absent price-shifter shocks detailed below, prices of the risky assets each follow:

$$\frac{d\tilde{P}_{j,t}}{\tilde{P}_{j,t}} = \mu_j dt + \sigma_{j,A} dB_{A,t} + \sigma_{j,I} dB_{j,t}, \quad (2)$$

where $dB_{A,t}$ represents a common “aggregate” shock and $dB_{j,t}$ an asset-specific shock. The Brownian motions $dB_{A,t}$ and $\{dB_{j,t}\}_{j=1}^J$ are mutually independent. The actual trading prices can be further affected by price-shifter shocks. Specifically, the equilibrium trading price $P_{j,t}$ of asset j satisfies

$$P_{j,t} = e^{\beta_j s_t} \tilde{P}_{j,t}, \text{ with } s_t \in \Omega \quad (3)$$

where $\beta_j s_t$ represents a log price shift applying to asset j , as similarly defined in [Binsbergen and Opp \(2019\)](#) and [Binsbergen et al. \(2023\)](#), Ω denotes the discrete set of possible shifter states s_t , and β_j governs the exposure of asset j to the shifter-state process $\{s_t\}_{t=0}^\infty$. In Section 3.3, we formally derive the outside group's residual supply dynamics that yield the postulated prices $P_{j,t}$ in equilibrium.

Event dates. To allow for well-defined demand elasticity estimation using discrete price shifts in a continuous-time setting, we introduce discrete event dates. At these points in time, price shifts may build up or change and agents may consume (disperse capital). While we initially consider the case in which agents can trade continuously, we will also analyze the setting in which trading is restricted to these discrete event dates. Event dates occur at the jump times τ_n of a Poisson process N_t with intensity $\lambda > 0$. The parameter λ allows us to freely adjust the average frequency at which these events occur.

At each event date, the following ordered events occur:

1. **Price wedge state transitions.** The wedge state w moves to w' with the Markov transition probabilities $q(s'|s)$.
2. **Consumption.** With probability π_C , existing CRRA investors exit and are replaced by a new cohort with identical post-jump wealth W' . Exiting investors liquidate their assets and consume their wealth W' . At the same time, newly entering investors purchase assets with their wealth W' .
3. **Portfolio choice.** Let $\theta = (\theta_1, \dots, \theta_J)^\top$ be the vector of portfolio shares invested in the J risky assets; the fraction in the risk-free asset is $\theta_0 = 1 - \mathbf{1}^\top \theta$. CRRA investors choose their risky shares θ_{τ_n} .

A portfolio policy θ_t is $\{\mathcal{F}_t\}$ -adapted and square-integrable. To guarantee positive wealth in the presence of price jumps, the admissible set in the case of continuous trade is defined as

$$\Theta(s) = \{\theta : 1 + \theta^\top \kappa_{s,s'} > 0 \ \forall s' \text{ with } q(s'|s) > 0\}. \quad (4)$$

3 Analysis

In this section, we first characterize CRRA investors' optimal portfolio policies under the postulated price dynamics. Second, we examine the difference between true demand elasticities and estimators derived from holdings data. Third, we close the model by characterizing the residual supply shock dynamics induced by a second group of outside agents that yield the postulated price dynamics in equilibrium.

3.1 Value Function and Optimal Trading

Over a small horizon dt , absent an event date, only diffusive risk is borne by the CRRA investors and wealth dynamics are given by:

$$\frac{dW_t}{W_t} = r_f dt + \sum_{j=1}^J \theta_{j,t} \left[(\mu_j - r_f) dt + \sigma_{j,A} dB_{A,t} + \sigma_{j,I} dB_{j,t} \right]. \quad (5)$$

Define the covariance matrix

$$\Sigma = \sigma_A \sigma_A^\top + \text{diag}(\sigma_{1,I}^2, \dots, \sigma_{J,I}^2), \quad \sigma_A := (\sigma_{1,A}, \dots, \sigma_{J,A})^\top.$$

Then $\text{Var}[dW_t/W_t] = \theta^\top \Sigma \theta dt$. Upon the arrival of an event date, a jump in the shifter state w may occur. Finally, with probability π_C , a CRRA agent liquidates its assets and consumes post-jump wealth W' . Otherwise, with complementary probability $(1 - \pi_C)$, the agent continues and a new portfolio is chosen.

Let $V(W, s)$ be the continuation value immediately after an event sequence. We obtain the Hamilton–Jacobi–Bellman (HJB) equation

$$0 = \max_{\theta} \left\{ -\rho V + V_W W \left[r_f + (\mu - r_f \mathbf{1})^\top \theta \right] + \frac{1}{2} V_{WW} W^2 \theta^\top \Sigma \theta + \lambda \mathbb{E} \left[\pi_C (u(W') - V(W, s)) + (1 - \pi_C) (V(W', s') - V(W, s)) \right] \right\}, \quad (6)$$

where W' denotes post-jump wealth:

$$W' = W \left[1 + \theta^\top \kappa_{s,s'} \right], \quad s' \sim q(\cdot | s), \quad (7)$$

and where we define:

$$\kappa_{s,s'}^{(j)} := e^{\beta_j(s'-s)} - 1, \quad \kappa_{s,s'} := (\kappa_{s,s'}^{(1)}, \dots, \kappa_{s,s'}^{(J)})^\top. \quad (8)$$

We conjecture and verify that the value function takes the form

$$V(W, s) = u(W) \cdot A(s). \quad (9)$$

Substituting $V_W = W^{-\gamma}A(s)$ and $V_{WW} = -\gamma W^{-\gamma-1}A(s)$ into (6) and dividing by $u(W)$ yields the following system of equations solved by the function $A(s)$ for $s \in \Omega$:

$$\begin{aligned} 0 = & -\rho A(s) + (1 - \gamma)A(s) \left[r_f + (\boldsymbol{\mu} - r_f \mathbf{1})^\top \boldsymbol{\theta} - \frac{1}{2} \gamma \boldsymbol{\theta}^\top \boldsymbol{\Sigma} \boldsymbol{\theta} \right] \\ & + \lambda \left[\sum_{s'} q(s'|s) [\pi_C + (1 - \pi_C)A(s')] \cdot (1 + \boldsymbol{\theta}^\top \kappa_{s,s'})^{1-\gamma} - A(s) \right]. \end{aligned} \quad (10)$$

Differentiating (10) with respect to each θ_j and dividing by $(1 - \gamma)$ yields the first-order conditions for all $j = 1, \dots, J$:

$$\begin{aligned} 0 = & A(s) \left[(\mu_j - r_f) - \gamma(\boldsymbol{\Sigma} \boldsymbol{\theta})_j \right] \\ & + \lambda \sum_{s'} q(s'|s) [\pi_C + (1 - \pi_C)A(s')] \cdot \kappa_{s,s'}^{(j)} \cdot (1 + \boldsymbol{\theta}^\top \kappa_{s,s'})^{-\gamma}. \end{aligned} \quad (11)$$

When none of the assets are exposed to the shifter state ($\beta_j = 0$ for all j), equation (11) collapses to the usual Merton (1969) condition for optimal portfolio shares. However, more generally, the additional term related to shifter-state transitions persists. Importantly, an analogous term also appears under log utility (see Appendix A.1), so it should not be interpreted as a mere intertemporal hedging motive. Rather, it reflects discrete changes in the shifter state w at event times. Together, equation (10) and the J first-order conditions (11) determine the functions $A(s)$ (for $s \in \Omega$) and the optimal risky-share vector $\boldsymbol{\theta}^*(s)$.

3.2 Demand Elasticity Estimates and Biases

In this section, we examine under what conditions true demand elasticities can be accurately estimated based on holdings data and what biases arise if such conditions are violated.

True price elasticities and the frequency of trade. As a first step, we show that the frequency with which agents can trade has relevant implications for the magnitudes of true demand elasticities. In our baseline setup, agents can trade continuously, which is a useful benchmark that increases analytical tractability. Yet, given various practical limitations to truly continuous trade, we are also interested in examining elasticities when institutions can trade only at discrete dates, such as at a daily frequency. Correspondingly, we start by characterizing the true own-price elasticity in two cases: (i) continuous trade and (ii) discrete trade occurring only upon the event dates τ_n .

Proposition 1. *Suppose there is one risky asset. In the case of continuous trading, the own-price elasticity is infinite,*

$$\varepsilon_C = -\frac{\partial \ln \theta_t^*}{\partial \ln P_t} = \infty. \quad (12)$$

In contrast, if agents can trade only upon the discrete event dates τ_n , the elasticity takes finite values

$$\varepsilon_D = -\frac{\partial \ln \theta_t^*}{\partial \ln P_t} < \infty, \quad (13)$$

and satisfies for short expected trading intervals: $\varepsilon_D/\lambda \approx \frac{[\pi_C + (1-\pi_C) \cdot A]}{(\mu - r_f) \cdot A}$ with

$$A := \lambda \pi_C \cdot \left(\lambda \pi_C + \rho - (1 - \gamma) \left[r_f + \frac{(\mu - r_f)^2}{2\gamma\sigma^2} \right] \right)^{-1}. \quad (14)$$

Proof. See Appendix A.2. □

In the limiting case of continuous trade, true price elasticities are infinite. This result obtains for the following reasons. An own-price elasticity quantifies how a marginal log-change to the contemporaneous price affects demand, keeping unchanged future prices at which an agent can resell the asset. In the case of continuous trade, this definition means that a log price shift $\xi := d \ln P$ at time t needs to resolve by the next instant $(t + dt)$, implying an incremental instantaneous resolution return $-\xi$ that lowers the expected rate of return relative to the baseline level of μ . This discrete change in the expected return of the risky asset from μ to $(\mu - \xi)$

implies a discrete (non-marginal) tilt in the optimal portfolio share θ^* .⁵ Correspondingly, a *marginal* price shift causes *discrete* portfolio share adjustment, leading to the result of an infinite price elasticity under continuous trade.

In contrast, the second part of Proposition 1 shows that elasticities are finite when agents can trade only at discrete dates. The reason is that a marginal price shift $\xi = d \ln P$ at time t then resolves over a discrete period of time, leading to only a marginal adjustment in the trading period's expected return. Correspondingly, now a *marginal* price shift induces only a *marginal* tilt in the portfolio share θ , yielding a finite elasticity.

In sum, substantial differences between discrete trading and continuous trading emerge since the resolution of a given contemporaneous price shift has a more muted impact on returns per unit of time when trading dates are less frequent.

Estimating elasticities with price-shifter processes. We now examine the elasticity estimates an econometrician would obtain when using instrumented price variation induced by incremental exposures to a general price-shifter state process $\{s_\tau\}_{\tau=t}^\infty$. Because $\ln P_j = \beta_j s + \ln \tilde{P}_j$, a one-unit change in the exposure β_j causes an s_t -unit change in the log price of asset j at time t . We then define the state-exposure elasticity:

$$\eta_j(s_t) := -\frac{1}{s_t} \frac{d \ln \theta_j^*(s_t)}{d \beta_j} \Big|_{\beta_j=0}. \quad (15)$$

This expression measures how the date- t optimal portfolio share, θ_t^* , responds to a marginal exposure to the shifter-state process $\{s_\tau\}_{\tau=t}^\infty$. Importantly, while the initial price shift is $d\beta_j s_t$ (as seen in the denominator), the date- t portfolio share θ_t^* generally responds to the dynamics of the entire future path of price shifts $\{d\beta_j s_\tau\}_{\tau=t}^\infty$. Moreover, a state-exposure elasticity is specific to the dynamic properties of the state process associated with a given instrument, $\{s_\tau\}_{\tau=t}^\infty$, and generally captures changes to the asset's fundamentals (which, in a dynamic trading environment, include other agents' future willingness to pay).

While empirical variation creating an exposure to such a state process can help identify the state-exposure elasticity (15), the requirement for own-price elasticity

⁵Note that the tilt is not infinite in magnitude due to asset's risk exposures.

identification are significantly more stringent. The following lemma details three conditions under which econometricians can infer the own-price elasticity from an incremental exposure of an asset to a shifter-state process $\{s_\tau\}_{\tau=t}^\infty$.

Lemma 1. *The own-price elasticity for asset j can be inferred from holdings data via variation in the asset's exposure to the shifter-state process $\{s_\tau\}_{\tau=t}^\infty$ if the following properties are satisfied:*

1. *The incremental price shift at time t fully and permanently resolves by the next trading date.*
2. *The exposure change is unanticipated.*
3. *The exposure change moves only the price of asset j , while leaving all other prices unaffected, $\beta_{\neq j} = 0$.*

The lemma lays out three conditions for identification. First, variation used for estimation must leave prices at future trading dates (resale values) unaffected. Otherwise, it alters the fundamental characteristics of the asset by changing the future cash flows it can deliver to the investor. This requirement applies equally to time-series and cross-sectional identification strategies. The issue is that *any* variation inducing changes in resale values *after* the date when portfolio holdings are observed and used for estimation effectively alters an asset's intrinsic characteristics (its exposure to state dynamics) — not just the current asset price — and thus directly violates the exclusion restriction.⁶

Second, time-series variation inducing a price change at time t and used for estimation must be unanticipated by investors since otherwise, the associated holdings change does not just reflect a date- t price change but also previous expectations of that price change, resulting in biased elasticity estimates. For instance, if a positive price shift was already expected to occur, then the optimal pre-shock holding is elevated due the prospect of an incremental positive return. As a result, after the

⁶KY's "identification comes from cross-sectional variation in the investment universe and not from time-series variation in assets moving in and out of the investment universe." KY acknowledge that they "maintain the assumption that the wealth distribution across other investors is predetermined and exogenous to current demand shocks." and that "this assumption ultimately appeals to a static view of portfolio choice."

positive price shift has realized, the portfolio weight would decline more than it otherwise would, and the elasticity estimate based on time-series changes would be biased upwards (if this were the only deviation from Lemma 1).

Third, to isolate the own-price elasticity, the variation exclusively affects the price of the asset under consideration. A simultaneous change in other asset prices would generally introduce cross-asset substitution effects into the elasticity estimate. This third condition of Lemma 1 relates to the ongoing debate about conditions under which shocks affecting multiple assets can properly identify own-price elasticities in static settings (see Fuchs et al., 2025; Haddad et al., 2025b; Kojen and Yogo, 2025). We note that condition 3 is not per se necessary for identification in all environments. Rather than investigating the generality and empirical plausibility of specific substitution structures, our paper focuses on identification issues arising in the context of environments where long-lived assets such as equities are dynamically traded (e.g., by mutual funds). In these settings, conditions regarding price shift dynamics as laid out in points 1 and 2 of Lemma 1 are crucial (see also Section 4), irrespective of the particular cross-sectional substitution preferences.

We now explicitly investigate how violations of the first condition of Lemma 1 impact elasticity estimates. The following proposition compares the true demand elasticity under discrete trading, ε_D , to the elasticity estimates obtained based on a shock that introduces a price shift that persists for multiple trading periods, thus violating condition 1 of Lemma 1.

Proposition 2 (Gradual price-shift resolution). *Suppose conditions 2 and 3 of Lemma 1 are satisfied and that there is one risky asset. Further, trade can occur only on event dates τ and a marginal log price shift away from the price level $\tilde{P}$ fully and permanently resolves with the per-event resolution probability π_R . We obtain the following relations between the true elasticity ε_D and the elasticity estimated from this price shift:*

1. **One-period shifts:** For $\pi_R = 1$, condition 1 of Lemma 1 is satisfied and estimated elasticity coincides with the true elasticity,

$$\hat{\varepsilon} = \varepsilon_D. \tag{16}$$

2. **Persistent shifts:** For $\pi_R < 1$, the demand elasticity estimated from variation in

the wedge state is biased toward zero. For short trading periods (large λ), the following relation obtains:

$$\frac{\hat{\varepsilon}}{\varepsilon_D} \approx \pi_R. \quad (17)$$

3. **Permanent shifts:** The demand elasticity estimated from permanent price level shifts is zero,

$$\hat{\varepsilon} = 0. \quad (18)$$

Proof. See Appendix A.2. □

The proposition reveals that the per-period resolution probability π_R is directly linked to the bias in elasticity estimates. As an illustration, suppose an institutional investor can trade daily, and a price shift used for identification persists for two years on average. Then, the estimated elasticity would underestimate the true elasticity dramatically, in this case by a factor of $1/730 = 0.14\%$. Thus, seemingly small persistence can significantly bias elasticity estimates downward.

Next, we turn to another important scenario, momentum-type price-shift dynamics, to highlight their particularly severe implications for elasticity mismeasurement. As we will show in our empirical analysis in Section 4, such dynamics are potentially relevant in the context of KY19's instrumented prices.

Proposition 3 (Momentum dynamics). *Suppose that conditions 2 and 3 of Lemma 1 are satisfied and that there is one risky asset. Further, trade can occur only on event dates τ . After an unanticipated log price shift $d\beta$ away from $\tilde{P}$, the price shift builds up to $2d\beta$ with probability π_B per event period before permanently and fully resolving back to the initial level $\tilde{P}$, with probability π_R . For short trading periods (large λ), we obtain the following relations between the true elasticity ε_D and the elasticity estimated from the initial price shift:*

$$\frac{\hat{\varepsilon}}{\varepsilon_D} \approx -\pi_B. \quad (19)$$

Proof. See Appendix A.3. □

Proposition 3 reveals the severe biases that variation triggering momentum dynamics introduce into elasticity estimates. Momentum causes investors to anticipate further price increases, thereby reversing their portfolio response compared to a pure contemporaneous price increase. Consequently, estimated elasticities are opposite in sign to the true elasticity. The more likely the subsequent build-up (π_B) the more extreme is the bias.

3.3 Equilibrium Pricing and Asset Purchase Programs

In this section, we first close the model by characterizing the supply shock dynamics that sustain the postulated price dynamics and portfolio problem described in Sections 2 and 3.1. The construction is deliberately minimal and ensures that no new state variables beyond s_t are introduced into CRRA investors' maximization problem.⁷ We then proceed to characterize how price elasticities and state-exposure elasticities relate to the multipliers discussed in the literature and derive the dynamic asset purchase programs required to induce a given stochastic price path differential in equilibrium.

3.3.1 Supply Behavior of the Outside Bloc

Let x_j denote a baseline number of shares outstanding of asset j . At any time t , denote by θ_j^* the optimal portfolio share invested in asset j by the unit mass of CRRA investors, and let s_t be their aggregate wealth. The outside group chooses its unit position according to

$$m_{j,t} = x_j - \frac{\theta_{j,t}^* W_t}{P_{j,t}}, \quad j = 0, \dots, J, \quad (20)$$

which implies unit market clearing at every instant:

$$n_{j,t} + m_{j,t} = x_j, \quad \text{with} \quad n_{j,t} := \frac{\theta_{j,t}^* W_t}{P_{j,t}} \quad j = 0, \dots, J. \quad (21)$$

⁷In general, in an economy with heterogeneous agents, the wealth distribution emerges as a relevant state variable.

Consequently, the law of motion of s_t and the transition matrix $q(s'|s)$ specified in Section 2 fully describe the evolution of equilibrium price shifts relative to the price level $\tilde{P}_j$. No separate tracking of the outside group's wealth or portfolio is necessary.

The idea that stochastic supply shocks generate price movements dates back at least to Grossman and Stiglitz (1980). In a dynamic context, Greenwood and Vayanos (2014) examine a term-structure model in which risk-averse arbitrageurs absorb shocks to the demand and supply for bonds of different maturities. The present model similarly captures such shocks but reverse engineers their magnitudes so as to match the equilibrium price dynamics postulated in Section 2.

Several familiar economic mechanisms can rationalize the sources of such supply shocks. In particular, the outside group of agents affecting supply may consist of noise traders, central banks, or corporations engaging in state-contingent share issuance or repurchases.

3.3.2 Elasticities, Multipliers, and Dynamic Asset Purchase Programs

In this section, we investigate how elasticities, which are partial equilibrium objects pertaining to specific investors, relate to multipliers, which quantify the impact of purchases on equilibrium market prices. In its simplest form, a multiplier measures how the market capitalization of an asset changes when a particular type of investor engages in a one-period purchase of the asset.

As we emphasize below, once we move to dynamic purchase programs, the concept of a multiplier measuring the initial price impact of a purchase becomes problematic. This is because the entire stochastic path of future purchase commitments, rather than the initial transaction, drives the price adjustment at the time of the program's announcement. Indeed, a dynamic purchase program involving no purchases upon impact can still have large effects on equilibrium prices simply by altering expected future resale values.

Price elasticities and one-period purchases. Suppose the outside block purchases an additional marginal unit of asset j . Starting from the market-clearing condition in

changes:

$$dm_{j,t} = -\frac{dn_{j,t}}{dP_{j,t}} dP_{j,t}, \quad (22)$$

we obtain the following relation by multiplying both sides by x_j and $P_{j,t}$ and rearranging terms:

$$\underbrace{\frac{dP_{j,t}}{P_{j,t}}}_{\text{Market cap change}} = \underbrace{\frac{dm_{j,t}}{x_j}}_{\text{Investment}} \cdot \underbrace{\left[-\frac{d \ln n_{j,t}}{d \ln P_{j,t}} \cdot \frac{n_{j,t}}{x_j} \right]^{-1}}_{\text{Multiplier}}. \quad (23)$$

That is, the relative change in the equilibrium price is given by the product of the fraction of shares outstanding purchased and the multiplier. The multiplier is the inverse of the product of CRRA investors' price elasticity of unit demand, $-\frac{d \ln n_{j,t}}{d \ln P_{j,t}}$, and their existing ownership footprint, $\frac{n_{j,t}}{x_j}$. The latter term measures the size of market participants that can take the other side of the outside block's trades.

Note that a change in the price $P_{j,t}$ also induces adjustments in CRRA investors' holdings of other assets $i \neq j$. Therefore, the outside block must compensate for these spillover adjustments in order to keep the prices of other assets unaffected.

It is further useful to characterize the relationship between the price elasticity of unit demand and the price elasticity of the portfolio weight ε . Using the identity $n_{j,t} = \frac{\theta_{j,t}^* W_t}{P_{j,t}}$, we obtain:

$$\begin{aligned} -\frac{d \ln n_{j,t}}{d \ln P_{j,t}} &= -\left(\frac{d \theta_{j,t}^*}{d P_{j,t}} \frac{W_t}{P_{j,t}} + \frac{d W_t}{d P_{j,t}} \frac{\theta_{j,t}^*}{P_{j,t}} - \frac{W_t}{P_{j,t}} \frac{\theta_{j,t}^*}{P_{j,t}} \right) \frac{P_{j,t}}{n_{j,t}} \\ &= \varepsilon_{j,t} + 1 - \theta_{j,t}^*. \end{aligned} \quad (24)$$

The difference between the two elasticity concepts arises from the fact that the impact of a price increase on unit demand can be decomposed into three channels: its effect on the portfolio weight, its effect on the investor's wealth level, and the direct mechanical effect of making the asset more expensive.

Dynamic purchase programs and multipliers. We now examine how the unanticipated initiation and public announcement of a dynamic purchase program affects asset price dynamics.

Proposition 4. *The unanticipated initiation and public announcement of the following process of incremental holdings by the outside block is necessary to induce a stochastic log price path differential $\{d\beta_j s_\tau\}_{\tau=t}^\infty$ for asset j :*

$$\left\{ \frac{dm_{j,\tau}}{x_j} \right\}_{\tau=t}^\infty = \left\{ d\beta_j s_\tau \cdot [\eta_{j,\tau} + (1 - \theta_{j,\tau}^*)] \cdot \frac{n_{j,\tau}}{x_j} \right\}_{\tau=t}^\infty. \quad (25)$$

Proof. See Appendix A.4. □

While asset j 's market price appreciates by $s_t d\beta_j$ upon announcement of the purchase program, this effect is sustained by the full process of incremental unit holdings $\{dm_{j,\tau}\}_{\tau=t}^\infty$, as detailed in equation (25). Among other factors, this process depends on the dynamics of state-exposure elasticities $\{\eta_j(s_\tau)\}_{\tau=t}^\infty$ as defined in equation (15), the buyer footprints $\{n_{j,\tau}/x_\tau\}_{\tau=t}^\infty$, and their portfolio shares $\{\theta_{j,\tau}^*\}_{\tau=t}^\infty$. In other words, the multiplier, defined as the ratio of the relative price appreciation to the initial fraction of shares purchased,

$$\frac{s_t d\beta_j}{dm_{j,t}/x_j} = [(\eta_{j,t} + (1 - \theta_{j,t}^*)) \cdot n_{j,t}/x_t]^{-1}, \quad (26)$$

does not actually reveal the future purchases that are ultimately necessary to induce the initial price reaction. To illustrate this issue, we examine in Case Study 1 below the example of purchase program announcements, such as those sometimes initiated by central banks.

Moreover, because the program is intended to affect only the price dynamics of asset j , the outside block must also adjust its holdings in other assets to compensate for substitution effects by CRRA investors. We will explore this issue in more detail in Case Study 2 below.

Case Study 1: Purchase Program Announcements

Central bank announcements of asset purchase programs provide a useful and relevant example illustrating the limited informational content of multipliers. Suppose the Federal Reserve announces that it will purchase an asset in future states of the world at prices higher than would prevail absent intervention. Anticipating this higher future resale value, the equilibrium price increases immediately at time t , even though the Federal Reserve does not purchase any assets at that time.

As a result, the multiplier measured at inception of the program (26) becomes infinite for any such announcement that promises *future* asset purchases. Yet, asset purchases are clearly not infinitely impactful—the multiplier is misleading and does not quantify the causal impact of date- t purchases on date- t equilibrium prices.

For CRRA investors to be content with a higher portfolio share in the asset (which results after the price increase), the expected return must rise. Consequently, momentum dynamics arise endogenously from such policy announcements, generally causing the state-exposure elasticity $\eta_{j,t}$ to become negative. This is not a special knife-edge case of merely theoretical relevance but rather a generic outcome for program announcements that do not immediately involve purchases upon inception, or feature dynamic position build-up. These issues underscore that estimating multipliers associated with dynamic residual supply shock processes is generally problematic and yields limited insights.

Case Study 2: Permanent Price Shifts

We now consider the special theoretical case of a constant and permanent log price shift affecting the entire stock market, an example also discussed in [Gabaix and Kojen \(2023\)](#). Our objective is to characterize the purchase quantity dynamics required to induce such a shift and to provide a simple calibration to gauge magnitudes. In this scenario, the shifter state is constant; that is, $s_\tau = 1$ for all $\tau \geq t$.

Suppose that the potential investors taking the other side of the purchases are CRRA investors with a relative risk aversion of 2 and initial holdings equal to 60% of shares outstanding, i.e., $n_{1,t}/x_{1,t} = 0.6$. Assume that, prior to the announcement of the dynamic purchase program, the market risk premium is 6%, volatility is 20%, and the dividend yield is 1.7%. In this setting, CRRA investors' risky portfolio share before the unanticipated intervention is then given by:

$$\theta_1^* = \frac{\mu_1 - r_f}{\gamma \sigma_1^2} = \frac{0.06}{2 \cdot 0.2^2} = 0.75. \quad (27)$$

Immediately after the onset of the asset purchase program, the expected return on the stock market declines due to a reduction in the dividend yield component of the

expected return:

$$\frac{d\mu_1}{d\beta_1} = \frac{d \frac{D_1}{\bar{P}_1 e^{\beta_1 \cdot 1}}}{d\beta_1} = -\frac{D_1}{P_1}. \quad (28)$$

Correspondingly, we obtain the following sensitivity of the portfolio share θ_1^* with respect to the exposure parameter β_1 :

$$\frac{d\theta_1^*}{d\beta_1} = \frac{-D_1/P_1}{\gamma \cdot \sigma_1^2} = -0.2125. \quad (29)$$

That is, for a 1% price shift, $\Delta\beta_1 = 0.01$, the risky portfolio share decreases from 0.75 to 0.748. We then obtain the following state-exposure elasticity:

$$\eta_1 = -\frac{1}{s} \frac{d \ln \theta_1^*}{d\beta_1} \Big|_{\beta=0} = \frac{D_1/P_1}{\mu_1 - r_f} = \frac{0.017}{0.06} = 0.28 \quad (30)$$

Further, converting this to the corresponding state-exposure elasticity in terms of unit demand gives $\eta_1 + (1 - \theta_1^*) = 0.53$. Substituting these values into equation (26) yields a multiplier upon impact (at time t) equal to:

$$\frac{d\beta_1}{dm_{1,t}/x_1} = [(\eta_{1,t} + (1 - \theta_{1,t}^*)) \cdot n_{1,t}/x_t]^{-1} = 3.14. \quad (31)$$

However, as emphasized earlier, it is the entire process of future holdings that induces the price increase at the inception of the program. In particular, equation (25) simplifies to the following dynamics for the incremental holdings of the intervening party:

$$\left\{ \frac{dm_{1,\tau}}{x_1} \right\}_{\tau=t}^{\infty} = \{d\beta_1 \cdot 0.53 \cdot n_{1,\tau}/x_1\}_{\tau=t}^{\infty}, \quad (32)$$

To raise the total market capitalization by $\Delta\beta_1 = 1\%$, the outside block must purchase $1\%/3.14 = 0.32\%$ of shares outstanding upon impact. Thereafter, it must adjust this incremental exposure dynamically, depending on how other investors' footprint, $n_{1,\tau}/x_1$, evolves over time as a consequence of their risky portfolio share θ_1^* and the stochastic realization of future stock market returns.

Moreover, to ensure that the purchase program does not also affect the price path

of the risk-free asset, the outside block must adjust its holdings as follows (see Appendix A.4):

$$\{dm_{0,\tau}\}_{\tau=t}^{\infty} = \left\{ -dm_{1,\tau} \frac{P_{1,\tau}}{P_{0,\tau}} \right\}_{\tau=t}^{\infty}. \quad (33)$$

Initially, at time t , the bond adjustment by the outside block merely funds its incremental stock market holding. However, for $\tau > t$, the outside block must step into any gap in risk-free asset holdings by CRRA investors, relative to the counterfactual. As a result, we obtain a stochastic process for bond holdings adjustments, $\{dm_{0,\tau}\}_{\tau=t}^{\infty}$, which depends on how the stock market performs relative to the risk-free asset, $\{P_{1,\tau}/P_{0,\tau}\}_{\tau=t}^{\infty}$, as well as on the process of stock market holdings adjustments, $\{dm_{1,\tau}\}_{\tau=t}^{\infty}$. For example, consider a path where the stock market outperforms the risk-free asset. In the counterfactual without intervention, CRRA agents would have become wealthier and increased their bond holdings over time. With the intervention, the outside block must offset this effect by progressively increasing its bond holdings as the stock market's relative valuation rises.

Overall, even in this stylized case, the asset purchase program is far more complex than what the multiplier suggests, as it requires managing an entire stochastic path of holdings in both risky and risk-free assets.

Case Study 3: Constant Per-Period Resolution Probabilities

As a final case study, we examine price shifter dynamics characterized by a constant per-period resolution probability. As shown in Section 3, the more persistent the price shifts are, the less CRRA investors optimally adjust their portfolio shares. Hence, by equation (20), persistent price movements can be supported by smaller variations in the outsiders' net supply, $m_{j,t}$, upon impact. In contrast, the transitory price dynamics required for identification under Lemma 1 induce larger swings in θ_j^* . To sustain such dynamics, the outside block must inject (or withdraw) correspondingly larger quantities of the asset. This leads to the following corollary.

Corollary 1 (Persistence and magnitudes of supply shocks). *Suppose the conditions laid out in Proposition 2 are satisfied. For a given marginal price shift that resolves with the per-event resolution probability π_R , the initial unit risky-asset demand*

change by outsiders satisfies

$$|dm_1(\pi'_R)| < |dm_1(\pi''_R)| \quad \text{for all } 0 \leq \pi'_R < \pi''_R \leq 1.$$

Proof. See Appendix A.5. □

While Corollary 1 pertains to the single-asset case, we illustrate the same mechanics for a multi-asset setting in Figure 1, with parameter values reported in Table 1. The shifter state w follows the resolution Markov chain described in Proposition 2. The figure plots the magnitude of supply shocks required upon impact to induce a given log price shift.

The results show that shock persistence, measured by the expected time to resolution, has a dramatic effect on the size of the required initial supply shock. The baseline “one-period” shock corresponds to a weekly event interval and assumes full resolution within that period. If, instead, the price shock persists for a quarter on average, the required supply shock upon impact falls to approximately 7%–8% of the one-period baseline. With an average duration of one year, the magnitude further declines to just 2%, and for a two-year resolution window, to less than 1%.

Simply put, more persistent shocks require much smaller supply interventions upon impact to achieve a given price shift, as CRRA investors’ optimal demand response is substantially muted when price changes are expected to persist. Importantly, these patterns do not reflect frictions that impede portfolio adjustments; rather, they arise endogenously from optimal dynamic trading behavior in response to changes in asset characteristics—specifically, the dynamics of expected resale values.

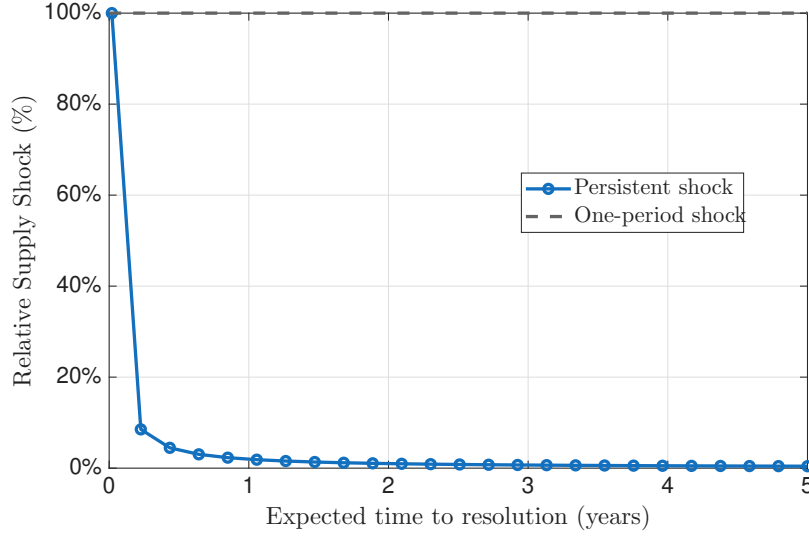


Figure 1: Supply Shock Magnitudes Upon Impact. The figure illustrates the magnitude of supply shocks required to induce a given log-price shift upon impact, as a function of the shock’s persistence, measured by the expected time to resolution, $\frac{1}{\lambda \pi_R}$. Throughout, the inception of supply shocks is assumed to be unanticipated. We plot the relative supply shock, $\frac{|\Delta m_j(\pi_R)|}{|\Delta m_j(1)|}$, where varying π_R adjusts the expected time to resolution. The shifter state w follows the resolution Markov chain described in Proposition 2. See Appendix A.6 for further details.

Table 1: Calibration and Relevant Statistics

Panel A. Investor preferences and timing			
Parameter	Symbol	Value	Unit / Note
Risk-free rate	r_f	0.04	annual
Subjective discount rate	ρ	0.02	annual
Relative risk aversion	γ	2	—
Event intensity	λ	52	weekly rebalancing opportunities
Consumption probability	π_C	0.002	per event date
Number of risky assets	J	3	—
Panel B. Asset characteristics (per risky asset j)			
Parameter	Symbol	Value	Unit / Note
Price drift (all j)	μ_j	0.09	$= r_f + 0.05$
Common-factor volatility	$\sigma_{A,j}$	(0.238, 0.190, 0.190)	per asset
Idiosyncratic volatility	$\sigma_{I,j}$	(0.300, 0.300, 0.300)	per asset
Log price shift	$\Delta\beta_1$	0.0011	—

4 Instrument Validity: Statistical Tests

In this section, we build on the insights from our theoretical analysis in Sections 2 and 3 and conduct a series of empirical tests to examine the characteristics and validity of the statistical instruments used in the literature—particularly those proposed by KY19. KY19 recover the slope of an investor’s demand schedule from a purely cross-sectional estimation. They define the instrument for the log market equity of asset n from the perspective of institution i as

$$\widehat{me}_i(n) = \log \left[\sum_{j \neq i} A_j \frac{\mathbf{1}_j(n)}{1 + \sum_{m=1}^N \mathbf{1}_j(m)} \right], \quad (34)$$

that is, the log market value of firm n under the counterfactual where all institutions other than i hold an equal-weighted portfolio within their investment universe.

As we explore the implications of time-series variation and predictability, we index the instrument by calendar time t and write $\widehat{me}_{i,t}(n)$. Throughout, we denote by $me_t(n)$ the actual log market value of asset n at time t , and by $\theta_{i,t}(n)$ the portfolio weight of institution i in asset n .

In KY19, the demand equation takes the form of a cross-sectional logit specification:

$$\frac{\theta_{i,t}(n)}{\theta_{i,t}(0)} = \exp\{\beta_{0,i,t}me_t(n) + \sum_{k=1}^{K-1} \beta_{k,i,t}x_{k,t}(n) + \beta_{K,i,t}\} \cdot \varepsilon_{i,t}(n), \quad (35)$$

where $x_{k,t}(n)$ denotes observable fundamental k for asset n at time t , and $\varepsilon_{i,t}(n)$ is an institution-asset-specific demand shifter (an unobserved taste shock). We stack the characteristics in the vector $\mathbf{x}_t(n)$.

Under KY19’s identifying assumptions, $\widehat{me}_{i,t}(n)$ serves as a valid instrument for $me_t(n)$: it shifts the supply curve but is assumed to be orthogonal to $\varepsilon_{i,t}(n)$, that is,

$$\mathbb{E}[\varepsilon_{i,t}(n) | \widehat{me}_{i,t}(n), \mathbf{x}_t(n)] = 0. \quad (36)$$

4.1 Descriptive Statistics

In constructing the dataset for our empirical analysis, we follow KY19 both in terms of data sources and data selection criteria. After excluding observations where size falls below the NYSE 10th percentile breakpoint, we compute time-series averages

of cross-sectional descriptive statistics (including percentiles) for various variables of interest. Table 2 reports these statistics for the stationary variables in our dataset. For non-stationary variables, we present corresponding statistics for successive five-year periods in Table 3. As in KY19, our sample period is 1980Q1-2017Q4, and all characteristics represent signals measured at quarter-end. Accounting variables are lagged by six months relative to market variables.

The reported variables are computed as follows. Profitability (*profit*) is defined as operating profits divided by book equity, where operating profits equal revenues (REVTS) minus cost of goods sold (COGS), SG&A expenses (XSGA), and interest expenses (XINT). Investment (*Gat*) is the annual log growth rate of book assets. The numerator in the dividend-to-book ratio (*divA_be*) is the sum of dividend payouts over the past 12 months.

Market betas (*beta*) are estimated using 60-month rolling windows, retaining quarter-end values. The book-to-market ratio (BtM) is computed as six-month-lagged book equity divided by end-of-quarter market capitalization. Book equity is calculated as stockholders' equity (SEQ), plus deferred taxes and investment tax credit (TXDITC), minus the redemption value of preferred stock (PSTKRV), and set to missing if the result is negative.⁸ The momentum return (MOM) at the end of quarter t is the compounded return over the past three quarters ($t-1, t-2, t-3$) plus the first two months of quarter t .

The component of the log market capitalization attributed to variation in $\widehat{me}$ is constructed as follows. For each quarter t , we run a cross-sectional regression of the form

$$me_t(n) = a_t + b_t \times \widehat{me}_t(n) + \mathbf{c}_t' \mathbf{x}_t(n) + \varepsilon_t(n), \quad (37)$$

where $\mathbf{x}_t(n)$ contains the four characteristics described above: *profit*, *Gat*, *divA_be*, and *beta*. We then compute $\hat{b}_t \times \widehat{me}_t(n)$ to extract the component of $me_t(n)$ attributable to variation in the instrument, controlling for the observables $\mathbf{x}_t(n)$.

⁸If SEQ is missing, we use the sum of common equity and preferred stock (CEQ + PSTK). If this is also missing, we use the difference between book assets (AT) and total liabilities (LT). If PSTKRV is missing, we use the liquidating value (PSTKL). If this is also missing, we use the total value of preferred stock (PSTK).

Table 2: Summary Statistics: Stationary Variables

Variable	Mean	Std	p25	p50	p75
PROF	0.21	0.24	0.13	0.22	0.32
INV	0.12	0.21	0.01	0.08	0.19
DIV	0.02	0.03	0.00	0.01	0.04
BETA	1.14	0.62	0.70	1.05	1.49
BtM	0.78	0.92	0.35	0.59	0.95
MOM	0.21	0.52	-0.06	0.13	0.36

Table 3: Summary Statistics: Non-Stationary Variables

Panel A: $\widehat{me}$							
Statistic	1980-85	1985-90	1990-95	1995-00	2000-05	2005-10	2010-17
Average CS Mean	4.07	5.08	5.75	6.47	7.27	7.83	8.36
Average CS P25	3.24	4.48	5.17	6.13	7.02	7.61	8.12
Average CS P50	4.15	5.09	5.75	6.50	7.30	7.79	8.31
Average CS P75	5.09	5.78	6.34	6.87	7.56	8.04	8.62
Average CS Std	1.32	0.91	0.78	0.63	0.48	0.38	0.48
Panel B: me							
Statistic	1980-85	1985-90	1990-95	1995-00	2000-05	2005-10	2010-17
Average CS Mean	5.50	5.93	6.02	6.52	6.90	7.44	7.74
Average CS P25	4.48	4.80	4.81	5.35	5.75	6.35	6.61
Average CS P50	5.28	5.70	5.76	6.21	6.60	7.15	7.51
Average CS P75	6.33	6.84	7.00	7.40	7.73	8.22	8.59
Average CS Std	1.24	1.36	1.48	1.46	1.47	1.38	1.43
Panel C: $\hat{b} \times \widehat{me}$							
Statistic	1980-85	1985-90	1990-95	1995-00	2000-05	2005-10	2010-17
Average CS Mean	3.23	5.39	7.33	8.05	10.48	13.50	14.43
Average CS P25	2.57	4.75	6.60	7.63	10.12	13.11	14.01
Average CS P50	3.29	5.39	7.33	8.09	10.52	13.42	14.34
Average CS P75	4.03	6.12	8.08	8.54	10.89	13.85	14.87
Average CS Std	1.04	0.95	0.99	0.78	0.70	0.66	0.82

For all three non-stationary variables, the average cross-sectional mean trends upward over time, as expected. Interestingly, while the cross-sectional dispersion of log size (me) remains roughly constant throughout the sample period, the cross-sectional spread (in log terms) of $\widehat{me}$ declines over time. This decline results in a narrowing cross-sectional spread of $\hat{b} \times \widehat{me}$.

4.2 Instrumented Market Equity and Future Returns

As highlighted in our theoretical analysis in Sections 2 and 3, investors' portfolio weights respond to price level shifts only to the extent that these shifts affect the return distribution going forward. In particular, for a myopic investor, the relevant return distribution is that up to the next trading date.

Correspondingly, we now examine how cross-sectional variation in instrumented market equity $\widehat{me}_{i,t}(n)$ induces cross-sectional variation in expected returns over different horizons, controlling for standard asset pricing factors commonly used by institutional investors.

If cross-sectional variation in $\widehat{me}_{i,t}(n)$ does not translate into resolution returns by the next trading date, a myopic investor's optimal portfolio weights will remain unresponsive to this variation. Consider, for example, two stocks with identical observable characteristics $\mathbf{x}_t(n)$, except that one is priced 1% higher, both today and at the next trading date. Absent dividends before the next trading date, both stocks offer identical return opportunities. As a result, a myopic investor will have no incentive to tilt her portfolio weights away from the higher-priced stock.

Moreover, dividends have quantitatively little impact on this baseline result. Consider, for example, a monthly rebalancing frequency. Suppose the “cheaper” stock has a monthly dividend yield of $\frac{D}{P} = 20$ basis points. Then, the dividend yield for the more expensive stock is $\frac{D}{P \times 1.01} = 19.8$ basis points. If the dividend yield accounts for 20% of the expected return, the two stocks would have expected returns of 100 basis points and 99.8 basis points, respectively — a difference of just 0.2 basis points. In other words, there is hardly any incentive to tilt portfolio weights, provided that both stocks are exposed to idiosyncratic risk.

In contrast, in the former case of persistent mispricing, we compare two assets that for all intents and purposes look identical from the perspective of a myopic investor. This example motivates empirically testing our key conditions for identifica-

tion, in particular, whether instrumented variation in market equity is associated with corresponding (full) resolution returns of the same magnitude over the next trading horizon.

Importantly, this response is entirely distinct from the case where the full cross-sectional price difference of 1% resolves by the next rebalancing date. In that case, the expensive asset’s expected return would be 100.2 basis points lower than that of the other asset, giving the investor a strong incentive to tilt away from the higher-priced stock. However, only this latter scenario identifies investors’ true demand elasticity. By contrast, in the case of persistent price level shifts, we are comparing two assets that, for all intents and purposes, appear identical to a myopic investor.

This example motivates our empirical tests of identification condition 1 of Lemma 1—specifically, whether instrumented variation in market equity is associated with corresponding (full) resolution returns of the same magnitude over the next trading horizon.

To begin, we examine the extent to which cross-sectional variation in instrumented market equity predicts future returns. Specifically, we estimate panel regressions of cumulative individual stock returns over various horizons H . Each excess-return regression takes the following generic form:⁹

$$R_{(t,H)}(n) = a_H + b_H \times \widehat{me}_t(n) + c_H \times \tilde{\mathbf{X}}_{n,t} + e_{n,t,H}$$

where $\tilde{\mathbf{X}}$ contains cross-sectionally standardized stock characteristics: log market equity, book-to-market ratio, momentum, investment, profitability, dividend-to-book ratio, and market beta. As the tables will show, some specifications include all components of $\tilde{\mathbf{X}}$, while others use only a subset.

In Table 4, each regressor is standardized as a within-period z-score. In Table 5, we alternatively map cross-sectional ranks onto the interval $[-1, 1]$ (see, e.g., Gu et al., 2020). Moreover, in Section 4.3, we consider a specification that does not apply any standardization.

We separately examine the extent to which cross-sectional dispersion at time t predicts returns over the first month (reflecting the initial trading period) and over subsequent periods. Specifically, we define the following four horizons: $H = 1$ month

⁹For these return predictability tests, we use the pooled version of instrumented market equity rather than the institution-specific version.

(return over the first month of quarter $t + 1$), $H = 1$ quarter (return over months 2 and 3 of quarter $t + 1$), $H = 4$ quarters (return over months 2 through 12), and $H = 6$ quarters (return over months 2 through 18).

To avoid overlapping data, we retain only every H -th observation within each PERMNO-specific time series. Standard errors are two-way clustered. The tables report coefficient estimates with p -values shown in parentheses. Further details on the data are provided in Appendix B.

The coefficient on instrumented market equity varies in sign depending on the control variables included and the return horizon considered. However, at the one-month horizon, the relationship between instrumented market equity and subsequent returns is consistently positive. Moreover, at longer horizons, the relationship remains positive whenever size (uninstrumented market equity), a standard asset pricing (or risk) factor widely used by institutional investors, is included as a control. In other words, a cross-sectional increase in a firm’s instrumented market equity is associated with *higher* average future returns.

While many of the coefficients on $\widehat{me}$ are positive, only some are statistically significant. In particular, coefficient estimates are significant when considering rank-standardized regressors (see Table 5) and including size as a control variable at the 1-month horizon. This pattern could justify tilts toward stocks with higher instrumented market equity, consistent with negative estimated elasticities when using this instrument. Indeed, in Section 4.4, we find that estimated elasticities are negative for a large fraction of stocks and institutions.

The coefficients on profitability (investment) are strongly positive (negative), consistent with the documented profitability premium and investment premium in the literature. Both are highly statistically significant. The coefficient on size is negative and statistically significant at horizons longer than one month. The coefficients on CAPM beta and dividends are generally insignificant. Finally, the coefficient on value is typically positive, consistent with the value premium, while the coefficient on momentum tends to be negative in these multivariate specifications.

Table 4: Return predictability regressions with z-score standardized regressors. The table reports panel regressions of excess returns on standard asset pricing characteristics (profitability, investment, dividends, beta, size, value, and momentum) as well as the instrumented log market equity $\widehat{me}$. The regressors are standardized in each period (z-scored). The table reports the coefficient estimates as well as the p -values in parentheses. The panels represent the following horizons: 1 month (return over the first month of quarter $t + 1$), one quarter (return over the last two months of quarter $t + 1$, i.e., months 2 and 3), 4 quarters (i.e., months 2 through 12) and 6 quarters (i.e., months 2 through 18).

	(a) One Month						(b) One Quarter						(c) Four Quarters						(d) Six Quarters						
Regressor	(a)	(b)	(c)	(d)	(e)	(f)	(a)	(b)	(c)	(d)	(e)	(f)	(a)	(b)	(c)	(d)	(e)	(f)	(a)	(b)	(c)	(d)	(e)	(f)	
$\widehat{me}$	0.22 (0.28)	—	0.56 (0.19)	0.21 (0.30)	0.19 (0.36)	0.45 (0.23)	-0.35 (0.17)	—	0.43 (0.40)	-0.35 (0.17)	-0.28 (0.28)	0.73 (0.15)	-0.11 (0.93)	—	4.08 (0.14)	-0.21 (0.87)	-0.34 (0.80)	3.52 (0.19)	0.10 (0.96)	—	6.13 (0.08)	-0.04 (0.98)	-0.33 (0.86)	5.04 (0.12)	
PROF	0.41 (0.03)	0.43 (0.02)	0.43 (0.02)	0.47 (0.02)	0.42 (0.02)	0.49 (0.01)	0.47 (0.04)	0.51 (0.03)	0.52 (0.03)	0.46 (0.06)	0.45 (0.05)	0.51 (0.04)	3.06 (0.00)	3.27 (0.00)	3.30 (0.00)	3.36 (0.00)	3.10 (0.00)	3.55 (0.00)	4.37 (0.00)	4.66 (0.00)	4.72 (0.00)	5.01 (0.00)	4.44 (0.00)	5.29 (0.00)	
INV	-0.31 (0.00)	-0.32 (0.00)	-0.29 (0.01)	-0.26 (0.01)	-0.31 (0.00)	-0.25 (0.02)	-0.72 (0.00)	-0.70 (0.00)	-0.68 (0.00)	-0.73 (0.00)	-0.72 (0.00)	-0.67 (0.00)	-2.82 (0.00)	-2.77 (0.00)	-2.57 (0.00)	-2.61 (0.00)	-2.80 (0.00)	-2.41 (0.00)	-4.37 (0.00)	-4.31 (0.00)	-4.02 (0.00)	-3.96 (0.00)	-4.34 (0.00)	-3.68 (0.00)	
DIV	-0.05 (0.57)	-0.02 (0.77)	-0.03 (0.75)	-0.02 (0.83)	-0.06 (0.53)	-0.01 (0.94)	-0.12 (0.35)	-0.06 (0.61)	-0.07 (0.60)	-0.13 (0.36)	-0.11 (0.40)	-0.04 (0.77)	-0.86 (0.13)	-0.55 (0.29)	-0.57 (0.27)	-0.72 (0.21)	-0.89 (0.12)	-0.48 (0.36)	-0.65 (0.50)	-0.22 (0.81)	-0.27 (0.78)	-0.38 (0.70)	-0.71 (0.46)	-0.11 (0.91)	
BETA	0.14 (0.53)	0.15 (0.49)	0.12 (0.58)	0.20 (0.37)	0.14 (0.53)	0.18 (0.40)	-0.21 (0.45)	-0.23 (0.41)	-0.25 (0.36)	-0.22 (0.41)	-0.21 (0.45)	-0.27 (0.31)	-0.81 (0.40)	-0.81 (0.39)	-1.05 (0.28)	-0.52 (0.56)	-0.79 (0.40)	-0.77 (0.40)	-0.72 (0.56)	-0.71 (0.58)	-1.09 (0.37)	-0.16 (0.89)	-0.67 (0.59)	-0.52 (0.66)	
SIZE	—	-0.00 (0.99)	-0.36 (0.33)	—	—	-0.28 (0.39)	—	-0.56 (0.00)	-0.84 (0.03)	—	—	-1.06 (0.01)	—	-1.80 (0.02)	-4.42 (0.02)	—	—	-4.04 (0.03)	—	-2.26 (0.07)	-6.22 (0.01)	—	—	-5.47 (0.01)	
VALUE	—	—	—	0.57 (0.01)	—	0.52 (0.01)	—	—	—	-0.12 (0.68)	—	-0.01 (0.96)	—	—	—	2.33 (0.01)	—	2.01 (0.02)	—	—	—	4.44 (0.00)	—	—	3.94 (0.00)
MOM	—	—	—	—	-0.19 (0.35)	-0.10 (0.58)	—	—	—	—	0.40 (0.11)	0.50 (0.03)	—	—	—	—	-1.19 (0.12)	-0.57 (0.43)	—	—	—	—	-2.21 (0.02)	-1.25 (0.15)	

Table 5: Return predictability regressions with rank-standardized regressors. The table reports panel regressions of excess returns on standard asset pricing characteristics (profitability, investment, dividends, beta, size, value, and momentum) as well as the instrumented log market equity $\widehat{me}$. The regressors are rank-standardized in each period. The table reports the coefficient estimates as well as the p -values in parentheses. The panels represent the following horizons: 1 month (return over the first month of quarter $t + 1$), one quarter (return over the last two months of quarter $t + 1$, i.e., months 2 and 3), 4 quarters (i.e., months 2 through 12) and 6 quarters (i.e., months 2 through 18).

	(a) One Month						(b) 1Q						(c) 4Q						(d) 6Q					
Regressor	(a)	(b)	(c)	(d)	(e)	(f)	(a)	(b)	(c)	(d)	(e)	(f)	(a)	(b)	(c)	(d)	(e)	(f)	(a)	(b)	(c)	(d)	(e)	(f)
$\widehat{me}$	0.36 (0.22)	—	1.35 (0.06)	0.33 (0.25)	0.31 (0.27)	1.08 (0.07)	-0.48 (0.18)	—	0.48 (0.55)	-0.49 (0.18)	-0.37 (0.30)	1.18 (0.13)	0.04 (0.98)	—	7.60 (0.09)	-0.13 (0.94)	-0.05 (0.98)	7.25 (0.10)	-0.22 (0.93)	—	9.47 (0.06)	-0.52 (0.84)	-0.55 (0.82)	7.30 (0.12)
PROF	0.47 (0.02)	0.50 (0.01)	0.53 (0.01)	0.85 (0.00)	0.50 (0.01)	0.86 (0.00)	0.68 (0.01)	0.73 (0.00)	0.74 (0.00)	0.81 (0.04)	0.59 (0.02)	0.87 (0.03)	3.56 (0.00)	3.86 (0.00)	3.99 (0.00)	5.61 (0.00)	3.63 (0.00)	5.76 (0.00)	4.81 (0.00)	5.17 (0.00)	5.33 (0.00)	8.66 (0.00)	5.05 (0.00)	8.79 (0.00)
INV	-0.41 (0.01)	-0.42 (0.00)	-0.33 (0.03)	-0.27 (0.06)	-0.42 (0.01)	-0.22 (0.11)	-1.03 (0.00)	-0.99 (0.00)	-0.95 (0.00)	-0.99 (0.00)	-1.03 (0.00)	-0.81 (0.00)	-3.80 (0.00)	-3.68 (0.00)	-3.17 (0.00)	-3.06 (0.00)	-3.80 (0.00)	-2.48 (0.00)	-5.80 (0.00)	-5.62 (0.00)	-5.00 (0.00)	-4.48 (0.00)	-5.83 (0.00)	-3.90 (0.00)
DIV	-0.06 (0.80)	0.03 (0.89)	0.04 (0.86)	-0.17 (0.48)	-0.07 (0.78)	-0.08 (0.71)	-0.16 (0.65)	-0.06 (0.86)	-0.06 (0.86)	-0.20 (0.55)	-0.14 (0.69)	-0.04 (0.89)	-1.17 (0.41)	-0.43 (0.75)	-0.39 (0.77)	-1.74 (0.21)	-1.19 (0.40)	-0.95 (0.44)	0.78 (0.74)	1.69 (0.46)	1.76 (0.44)	-0.19 (0.93)	0.73 (0.75)	0.65 (0.76)
BETA	0.20 (0.56)	0.24 (0.47)	0.13 (0.69)	0.34 (0.32)	0.19 (0.57)	0.28 (0.38)	-0.29 (0.48)	-0.32 (0.44)	-0.36 (0.39)	-0.24 (0.53)	-0.26 (0.53)	-0.26 (0.49)	-1.24 (0.38)	-1.12 (0.41)	-1.74 (0.23)	-0.42 (0.74)	-1.26 (0.37)	-0.86 (0.52)	-0.40 (0.84)	-0.28 (0.89)	-1.08 (0.58)	1.06 (0.60)	-0.45 (0.82)	0.47 (0.81)
SIZE	—	-0.14 (0.73)	-1.54 (0.11)	—	—	-1.16 (0.16)	—	-1.00 (0.02)	-1.50 (0.13)	—	—	-2.35 (0.01)	—	-3.83 (0.02)	-11.78 (0.02)	—	—	-11.13 (0.02)	—	-4.96 (0.05)	-14.89 (0.01)	—	—	-11.79 (0.01)
VALUE	—	—	—	—	0.91 (0.00)	0.85 (0.00)	—	—	—	0.30 (0.50)	—	0.57 (0.17)	—	—	—	4.78 (0.00)	—	4.64 (0.00)	—	—	—	8.72 (0.00)	—	8.31 (0.00)
MOM	—	—	—	—	-0.32 (0.02)	0.04 (0.89)	—	—	—	—	0.86 (0.02)	1.27 (0.00)	—	—	—	—	-0.69 (0.62)	1.78 (0.15)	—	—	—	—	-2.59 (0.13)	1.04 (0.49)

4.3 Resolution Tests

In the previous section, we examined panel regressions of cumulative individual stock returns at various horizons H on standard asset pricing factors, augmented with instrumented market equity. There, we normalized each variable either by ranking it and mapping it onto the interval $[-1, 1]$, or by standardizing it as a z-score.

In this section, we consider a specification that even more directly relates to Identification Condition 1 in Lemma 1—namely, that a price shift used for elasticity identification must resolve fully by the next trading date. To examine this quantitative restriction, we focus on the variable $\hat{b} \times \widehat{me}$, which, under the assumption that the instrument shifts prices for non-fundamental reasons (controlling for the observables X), captures the corresponding log price shift. Moreover, we no longer normalize variables in this analysis. Thus, if institutions can trade monthly, full resolution within that period would correspond to a coefficient of -1 on $(\hat{b} \times \widehat{me})$ at the one-month horizon.

The results are reported in Table 6. Qualitatively, the findings are similar to those reported earlier. Once again, the coefficient on instrumented market equity varies in sign depending on the control variables included and the return horizon considered. At the one-month horizon, the point estimates for the relationship between instrumented market equity and subsequent returns remain consistently positive across specifications. Moreover, at longer horizons, the relationship is typically positive whenever size (uninstrumented market equity) is included as a control.

Importantly, across all specifications in the table, we can reject the null hypothesis that the coefficient on $(\hat{b} \times \widehat{me})$ is -1 , with a p -value of 0.00.¹⁰ This provides direct evidence that the instrument fails to satisfy the full-resolution requirement for elasticity identification stated in Lemma 1.

¹⁰The p -values reported in the table refer to the null hypothesis of 0.

Table 6: Price shift resolution regressions. The table reports panel regressions of excess returns on standard asset pricing characteristics (profitability, investment, dividends, beta, size, value, and momentum) as well as $\hat{b} \times \widehat{me}$. Variables are not standardized. The table reports the coefficient estimates as well as the p -values corresponding to the null hypothesis of zero in parentheses. Across all specifications in the table, we can reject the null hypothesis that the coefficient on $(\hat{b} \times \widehat{me})$ is -1 , with a p -value of 0.00. The panels represent the following horizons: 1 month (return over the first month of quarter $t + 1$), one quarter (return over the last two months of quarter $t + 1$, i.e., months 2 and 3), 4 quarters (i.e., months 2 through 12) and 6 quarters (i.e., months 2 through 18).

	(a) One Month						(b) One Quarter						(c) Four Quarters						(d) Six Quarters						
Regressor	(a)	(b)	(c)	(d)	(e)	(f)	(a)	(b)	(c)	(d)	(e)	(f)	(a)	(b)	(c)	(d)	(e)	(f)	(a)	(b)	(c)	(d)	(e)	(f)	
$\hat{b} \times \widehat{me}$	0.04 (0.71)	—	0.09 (0.56)	0.06 (0.61)	0.03 (0.78)	0.08 (0.60)	-0.05 (0.69)	—	0.02 (0.89)	-0.05 (0.72)	-0.05 (0.71)	0.03 (0.85)	-0.10 (0.88)	—	0.23 (0.74)	-0.02 (0.98)	-0.18 (0.76)	0.14 (0.83)	-0.67 (0.37)	—	-0.24 (0.77)	-0.55 (0.44)	-0.79 (0.25)	-0.37 (0.62)	
PROF	1.24 (0.04)	1.30 (0.03)	1.37 (0.02)	1.56 (0.01)	1.18 (0.01)	1.55 (0.01)	0.96 (0.20)	1.16 (0.13)	1.17 (0.11)	1.03 (0.18)	0.97 (0.18)	1.27 (0.07)	7.95 (0.00)	8.69 (0.00)	8.81 (0.00)	9.58 (0.00)	7.43 (0.00)	9.44 (0.00)	12.73 (0.00)	14.07 (0.00)	13.95 (0.00)	15.31 (0.00)	11.70 (0.00)	14.75 (0.00)	
INV	-1.57 (0.07)	-1.65 (0.07)	-1.51 (0.09)	-1.14 (0.20)	-1.58 (0.07)	-1.17 (0.18)	-3.92 (0.00)	-3.86 (0.00)	-3.83 (0.00)	-3.82 (0.00)	-3.91 (0.00)	-3.72 (0.00)	-15.69 (0.00)	-15.67 (0.00)	-15.33 (0.00)	-13.73 (0.00)	-15.71 (0.00)	-13.92 (0.00)	-24.21 (0.00)	-23.29 (0.00)	-23.65 (0.00)	-21.48 (0.00)	-24.31 (0.00)	-21.72 (0.00)	
DIV	-0.14 (0.97)	0.12 (0.98)	1.96 (0.64)	1.89 (0.63)	-1.26 (0.74)	2.12 (0.63)	-9.23 (0.13)	-6.15 (0.37)	-5.73 (0.35)	-8.76 (0.16)	-9.02 (0.13)	-4.85 (0.44)	-34.65 (0.15)	-24.36 (0.45)	-19.35 (0.43)	-25.44 (0.31)	-41.11 (0.09)	-21.19 (0.39)	-29.71 (0.36)	-3.09 (0.94)	-8.47 (0.79)	-16.37 (0.62)	-39.48 (0.20)	-12.40 (0.69)	
BETA	0.30 (0.34)	0.32 (0.33)	0.29 (0.35)	0.39 (0.23)	0.35 (0.27)	0.42 (0.20)	-0.40 (0.27)	-0.40 (0.27)	-0.41 (0.25)	-0.37 (0.30)	-0.41 (0.25)	-0.40 (0.25)	-0.79 (0.60)	-0.79 (0.59)	-0.86 (0.56)	-0.27 (0.86)	-0.41 (0.78)	-0.12 (0.93)	-0.70 (0.68)	-0.87 (0.61)	-0.79 (0.64)	0.04 (0.98)	-0.04 (0.98)	0.40 (0.81)	
SIZE	—	—	-0.05 (0.72)	-0.18 (0.34)	—	-0.12 (0.48)	—	—	-0.27 (0.13)	-0.30 (0.04)	—	-0.30 (0.03)	—	—	-0.96 (0.23)	-1.27 (0.03)	—	-1.00 (0.06)	—	—	-2.04 (0.05)	-1.71 (0.04)	—	—	-1.23 (0.10)
VALUE	—	—	—	—	0.73 (0.02)	0.63 (0.03)	—	—	—	0.17 (0.41)	—	0.18 (0.31)	—	—	—	3.25 (0.00)	—	2.49 (0.00)	—	—	—	4.40 (0.00)	—	—	3.50 (0.00)
MOM	—	—	—	—	-0.94 (0.04)	-0.76 (0.07)	—	—	—	—	0.18 (0.74)	0.28 (0.61)	—	—	—	—	-5.37 (0.00)	-4.64 (0.00)	—	—	—	—	-9.22 (0.00)	-8.11 (0.00)	

4.4 Unrestricted Elasticity Estimates

The results in the previous section show that, in several specifications, the relationship between instrumented market equity and returns is positive, not negative. The idea that investors might allocate more to “expensive” stocks is consistent with the price-shift build-up patterns documented in the literature (see [Binsbergen et al., 2023](#)). For example, the momentum effect implies that expected returns are higher, in the cross-section, for stocks that have experienced large price increases (winners) compared to those with the largest price declines (losers). In a static framework, higher allocations to more expensive stocks, as measured by instrumented market equity, could therefore lead to erroneously estimated negative price elasticities.

KY19 impose the assumption that demand curves are downward sloping, that is, they restrict elasticities to be positive, by requiring $\beta_{0,i,t} < 1$. This constraint eliminates the possibility of negative elasticity estimates. In this section, we reestimate their demand equations without imposing this restriction to assess how binding the constraint is in practice.

As in KY19, we restrict the sample to institutions with at least 1,000 stock holdings at any given point in time. Over the sample period 1980Q1-2017Q4, this yields 9,289 institution-date pairs for which we estimate the demand equation.

Results. Panel A of Table 7 reports the unconstrained beta estimates of the demand equations for all institutions and time periods (columns 2 and 3) and compares them with the constrained estimates (imposing $\beta_{0,i,t} < 1$) in column 4, following KY19. Columns 2 and 4 use the institution-specific instruments ($\widehat{me}_{i,t}(n)$), while column 3 reports estimates based on the pooled instrumented market equity ($\widehat{me}_{HH,t}(n)$).

The table shows that in approximately 40-44% of cases, the unconstrained beta estimates violate KY19’s assumption that $\beta_{0,i,t} < 1$. The mean beta in the unconstrained estimation is 0.81, compared to 0.89 in the constrained case. The standard deviation of the estimates is 0.41 in the unconstrained case versus 0.25 in the constrained case.

According to KY19, for each date-manager pair, the point estimate of $\beta_{0,i,t}$ can be used to compute the matrix of cross-elasticities as follows:

$$\Psi_{i,t} = \mathbf{I} - \beta_{0,i,t} \text{diag}(\mathbf{w})^{-1} \times (\text{diag}(\mathbf{w}) - \mathbf{w}\mathbf{w}'), \quad (38)$$

Table 7: Summary Statistics for Estimated β s and Implied Elasticities

Statistic	Panel A: Estimated β s			Panel B: Implied Elasticities		
	$IVme$	$IVme_{HH}$	$IVme (\beta_{0,i,t} < 1)$	$IVme$	$IVme_{HH}$	$IVme_{HH} (\beta_{0,i,t} < 1)$
Mean	0.89	0.93	0.81	−0.04	−0.03	0.13
Std	0.41	0.37	0.25	0.37	0.42	0.24
p25	0.62	0.72	0.71	−0.26	−0.23	0.01
p50	0.90	0.95	0.94	−0.06	−0.06	0.01
p75	1.16	1.18	0.99	0.17	0.24	0.18
$P(\beta > 1)$	0.40	0.44	0.00	—	—	—
$E[\beta \mid \beta > 1]$	1.27	1.25	—	—	—	—
Proportion < 0	—	—	—	0.58	0.56	0.00

where $\mathbf{w}$ is the vector of positive portfolio weights for institution i at time t , and $\mathbf{I}$ and $\mathbf{w}$ have corresponding dimensions.

Focusing on the diagonal elements of $\eta_{i,t}$ across a random sample of 300 date-manager pairs (representing 549,250 such elasticities), we obtain the distribution of elasticities reported in Panel B of Table 7. For each distribution of beta estimates in columns 2, 3, and 4 of Panel A, we report the corresponding elasticity distributions in columns 2, 3, and 4 of Panel B.

The table shows that when we remove the constraint $\beta_{0,i,t} < 1$, the majority of elasticity estimates are negative, with both the mean and median of the distribution below zero.

4.5 Discussion on Learning and Beliefs

The tests above take the view that investors would, at best, respond to return predictability associated with the instrument only to the extent that it materialized ex post over the full sample period. A simpler explanation for a lack of responsiveness is that investors may never have attempted to investigate a signal equivalent to the instrument during the sample period, and thus would naturally not react to this variation, implying an observed elasticity around zero. Moreover, even if investors had explored such a signal, detecting statistically significant patterns would have been even harder given the shorter samples they had access to within our overall sample period. This, again, would result in a lack of responsiveness.

The only scenario where identification could succeed is if investors mistakenly

believed, throughout the entire sample period, that the cross-sectional price dispersion induced by $\widehat{me}$ would lead to fully resolving returns within a single trading period, even though this consistently failed to occur. However, invoking such a systematic misperception appears implausible.

5 Conclusion

In this paper, we demonstrate that prevailing approaches to estimating asset demand elasticities based on static structural IO models can generate substantial and systematic bias when applied to financial markets, whose “products” can be dynamically traded. When shocks that induce price shifts are persistent or generate return predictability, the exclusion restrictions necessary for identification are violated, rendering elasticity estimates non-informative or even misleading. Our theoretical framework clarifies the specific conditions under which elasticities can be meaningfully estimated and quantifies the magnitude of bias when these conditions fail. Empirically, we show that widely used instruments — such as KY19’s instrumented market equity — exhibit precisely the types of dynamic patterns that invalidate standard interpretations.

More broadly, our results call for a reassessment of how—and whether—elasticity estimates should be used to inform asset pricing models. Going forward, empirical research on demand sensitivity in financial markets must explicitly account for the temporal structure of trading and price formation. Failure to do so risks conflating dynamic optimization behavior with static inelasticity, leading to incorrect inferences about investor behavior and the functioning of financial markets.

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Appendix

A Additional Analyses and Proofs

A.1 The Case of Log Utility

For the case of log utility we conjecture and verify that the value function takes the form

$$V(W, s) = v \log W + A(s), \quad (39)$$

with $v \in (0, 1)$ chosen so that the HJB has no residual dependence on $\log W$. Substituting $V_W = v/W$ and $V_{WW} = -v/W^2$ into (6), using $W' = W(1 + \boldsymbol{\theta}^\top \boldsymbol{\kappa}_{s,s'})$ and $u(W') = \log W'$, gives

$$\begin{aligned} 0 = \max_{\boldsymbol{\theta}} \Big\{ & -\rho [v \log W + A(s)] + v \left[r_f + (\boldsymbol{\mu} - r_f \mathbf{1})^\top \boldsymbol{\theta} - \frac{1}{2} \boldsymbol{\theta}^\top \boldsymbol{\Sigma} \boldsymbol{\theta} \right] \\ & + \lambda \sum_{s'} q(s'|s) \left[\pi_C (\log W + \log(1 + \boldsymbol{\theta}^\top \boldsymbol{\kappa}_{s,s'}) - v \log W - A(s)) \right. \\ & \left. + (1 - \pi_C) (v \log W + v \log(1 + \boldsymbol{\theta}^\top \boldsymbol{\kappa}_{s,s'}) + A(s') - v \log W - A(s)) \right] \Big\}. \end{aligned}$$

Collecting the $\log W$ terms yields the coefficient

$$-\rho v + \lambda \pi_C (1 - v) = 0 \quad \Rightarrow \quad v = \frac{\lambda \pi_C}{\rho + \lambda \pi_C}.$$

The remaining terms (independent of $\log W$) give the system solved by $A(s)$:

$$\begin{aligned} 0 = & -\rho A(s) + v \left[r_f + (\boldsymbol{\mu} - r_f \mathbf{1})^\top \boldsymbol{\theta} - \frac{1}{2} \boldsymbol{\theta}^\top \boldsymbol{\Sigma} \boldsymbol{\theta} \right] \\ & + \lambda \sum_{s'} q(s'|s) \left[(1 - \pi_C) A(s') - A(s) + \tilde{C} \cdot \log(1 + \boldsymbol{\theta}^\top \boldsymbol{\kappa}_{s,s'}) \right], \end{aligned} \quad (40)$$

where we define:

$$\tilde{C} := \pi_C + (1 - \pi_C) v. \quad (41)$$

Differentiating (40) with respect to each θ_j yields the first-order conditions

$$0 = v \left[(\mu_j - r_f) - (\Sigma \theta)_j \right] + \lambda \tilde{C} \sum_{s'} q(s'|s) \frac{\kappa_{s,s'}^{(j)}}{1 + \theta^\top \kappa_{s,s'}}, \quad j = 1, \dots, J. \quad (42)$$

A.2 Proof of Propositions 1 and 2

Suppose that θ_C^* is the optimal portfolio share in the economy with continuous trade and θ_D^* the optimal portfolio share when agents can trade only upon the discrete event dates τ_n . Below we derive the results of Propositions 1 and 2 jointly. As stated in the Propositions, we consider one risky asset. We first consider the case of continuous trading. Thereafter, we analyze the setting with trading at the discrete event dates.

A.2.1 Continuous Trading

We first consider the continuous-trade economy and derive the sensitivity of the optimal risky-asset share $\theta_C^*(s)$ with respect to the exposure to the wedge state

$$\left. \frac{d\theta_C^*(s)}{d\beta} \right|_{\beta=0} \quad (43)$$

under the assumption of three shifter states $\{-1, 0, +1\}$ with transition probabilities

$$q(0|1) = q(0|-1) = \pi_R, \quad q(1|1) = q(-1|-1) = 1 - \pi_R, \quad q(0|0) = 1,$$

where all other Markov transition rates are zero. We consider only one risky asset. Thus, we drop the subscript “1” on $\mu_1, \sigma_{1,A}, \sigma_{1,I}$. Define the total variance

$$\sigma^2 := \sigma_A^2 + \sigma_I^2.$$

For any shifter state $s \in \{-1, +1\}$, the return if the wedge jumps to $s' = 0$ is:

$$\kappa(s) := \kappa_{s,0} = e^{\beta(0-s)} - 1 = e^{-\beta s} - 1.$$

Note that $\kappa(0) = 0$. Under the stated assumptions, the first-order condition (11) can be written as

$$0 = A(s) [\mu - r_f - \gamma \sigma^2 \theta_C(s)] + \lambda \pi_R C(0) \kappa(s) [1 + \theta_C(s) \kappa(s)]^{-\gamma}, \quad (44)$$

where we define:

$$C(s) := \pi_C + (1 - \pi_C)A(s). \quad (45)$$

No shift $s = 0$. Because the state $s = 0$ is absorbing, the FOC at $s = 0$ contains no jump term and yields the standard Merton share

$$\theta_C^*(0) = \frac{\mu - r_f}{\gamma \sigma^2}.$$

Further, $A(0)$ is independent of π_R because it is determined entirely in the absorbing state $s = 0$.

State-independence at $\beta = 0$. When $\beta = 0$ we have $\kappa_{s,s'} = 0$ for all states. Then the FOC reduces to

$$\mu - r_f - \gamma \sigma^2 \theta_C^*(s) = 0 \quad (46)$$

so $\theta_C^*(s) = \theta_C^*(0)$ is independent of w . Substituting this θ_C^* into (10) shows that a constant function $A(s) \equiv A(0)$ solves the corresponding linear system. Evaluating it at the absorbing state $s = 0$ pins down $A(0)$ via (10) (see the expression derived below).

Shifter states $s \in \{-1, +1\}$. Define

$$f(\theta, \beta; w) := A(s) [\mu - r_f - \gamma \sigma^2 \theta] + \lambda \pi_R C(0) \kappa(s) [1 + \theta \kappa(s)]^{-\gamma}.$$

The FOC (44) is $f(\theta_C(s), \beta; s) = 0$. At $\beta = 0$, as shown above, we have $A(s) = A(0)$ and $\kappa(s) = 0$, so

$$f(\theta, 0; s) = A(0) [\mu - r_f - \gamma \sigma^2 \theta], \quad (47)$$

yields $\theta_0 := \theta_C^*(0)$. Computing the partial derivatives at $(\theta_0, 0)$ yields:

$$\begin{aligned}\partial_\theta f(\theta_0, 0; s) &= -A(0)\gamma\sigma^2, \\ \partial_\beta f(\theta_0, 0; s) &= \lambda \pi_R C(0) \partial_\beta \left(\kappa(s) [1 + \theta_0 \kappa(s)]^{-\gamma} \right) \Big|_{\beta=0} = -\lambda \pi_R C(0) s,\end{aligned}\quad (48)$$

since $\partial_\beta \kappa(s)|_{\beta=0} = -s$ and the term from differentiating $[1 + \theta_0 \kappa]^{-\gamma}$ vanishes at $\kappa = 0$. By the implicit function theorem,

$$\frac{d\theta_C^*(s)}{d\beta} \Big|_{\beta=0} = -\frac{\partial_\beta f}{\partial_\theta f} \Big|_{(\theta_0, 0)} = -\frac{\lambda \pi_R C(0)}{A(0) \gamma \sigma^2} s. \quad (49)$$

It follows that the state-exposure elasticity is

$$\eta_C(s) = -\frac{1}{s} \frac{\frac{d\theta_C^*(s)}{d\beta}}{\theta_C^*(0)} \Big|_{\beta=0} = \pi_R \frac{\lambda C(0)}{(\mu - r_f) A(0)}. \quad (50)$$

With continuous trade, the true elasticity requires instantaneous and deterministic resolution, which obtains when $\lambda \rightarrow \infty$ and $\pi_R = 1$. It follows that the true price elasticity under continuous trade is $\varepsilon_C = \infty$.

Deriving $A(0)$. When state $s = 0$ is an absorbing state, equation (10) simplifies to:

$$\begin{aligned}0 &= -\rho A(0) + (1 - \gamma) A(0) \left[r_f + (\mu - r_f) \theta(0) - \frac{1}{2} \gamma \theta(0)^2 \sigma^2 \right] \\ &\quad + \lambda \left[[\pi_C + (1 - \pi_C) A(0)] - A(0) \right],\end{aligned}\quad (51)$$

and solving for $A(0)$ yields:

$$A(0) = \frac{\lambda \pi_C}{\lambda \pi_C + \rho - (1 - \gamma) \left[r_f + (\mu - r_f) \theta(0) - \frac{1}{2} \gamma \theta(0)^2 \sigma^2 \right]}. \quad (52)$$

Further, the optimal portfolio share is given by the Merton demand $\theta_C^*(0) = \frac{\mu - r_f}{\gamma \sigma^2}$. Substituting this result yields:

$$A(0) = \frac{\lambda \pi_C}{\lambda \pi_C + \rho - (1 - \gamma) \left[r_f + \frac{(\mu - r_f)^2}{2\gamma \sigma^2} \right]}. \quad (53)$$

A.2.2 Discrete Trading

To keep CRRA utility well-defined under discrete trading, we restrict attention to policies that keep wealth strictly positive, which corresponds to the restriction that at each event date a risky asset weight $\theta_D \in [0, 1]$ is chosen. Let the risk-free asset price be $P_{0,t}$ with $dP_{0,t}/P_{0,t} = r_f dt$. At an event time τ , a CRRA investor chooses a weight $\theta_D \in [0, 1]$ that corresponds to fixed units

$$n_1 = \frac{\theta_D W_\tau}{P_\tau}, \quad n_0 = \frac{(1 - \theta_D) W_\tau}{P_{0,\tau}}. \quad (54)$$

For $t \in [0, \Delta]$, we obtain:

$$\begin{aligned} W_t &= n_1 P_t + n_0 P_{0,t} = \theta_D W_\tau \frac{P_t}{P_\tau} + (1 - \theta_D) W_\tau \frac{P_{0,t}}{P_{0,\tau}} \\ &= \theta_D W_\tau \frac{P_t}{P_\tau} + (1 - \theta_D) W_\tau e^{r_f(t-\tau)} > 0 \quad \text{a.s.} \end{aligned} \quad (55)$$

since $P_t > 0$ and $P_{0,t} > 0$ almost surely. Let

$$\theta_C(0) = \frac{\mu - r_f}{\gamma \sigma^2} \in (0, 1) \quad (56)$$

be the Merton share under continuous trade and $s = 0$. We assume there exist $\underline{\lambda} < \infty$ and $\bar{\beta} > 0$ such that for all $\lambda \geq \underline{\lambda}$ and all $|\beta| \leq \bar{\beta}$ the optimal discrete-trade choice remains interior:

$$\theta_D^*(s; \lambda, \beta) \in (0, 1) \quad \text{for all } s \in \{-1, 0, +1\}. \quad (57)$$

Note that the perturbation we study below is local in β and our sensitivity result below shows that:

$$\theta_D^*(s; \lambda, \beta) = \theta_C(0) + o\left(\frac{1}{\lambda}\right) + o(\beta), \quad (58)$$

so for large enough λ and small enough $|\beta|$ the constraint $\theta_D \in [0, 1]$ is slack. Correspondingly, the unconstrained FOC and the elasticity results derived below apply.

Given a weight θ_D is chosen at the last event date, the post-event weight after time t has passed is given by:

$$\theta_t := \frac{\theta_D P_t}{\theta_D P_t + (1 - \theta_D) e^{r_f t}}.$$

Then $\{\theta_t\}_{t \geq 0}$ follows

$$d\theta_t = \theta_t(1 - \theta_t)(\mu - r_f - \sigma^2 \theta_t) dt + \sigma \theta_t(1 - \theta_t) dB_t, \quad \theta_0 = \theta_D. \quad (59)$$

Given the above assumptions, the post-event weight satisfies $\theta_t \in (0, 1)$ for $t \in [\tau, \tau + \Delta]$, that is, it is bounded, so

$$\mathbb{E} \left[\int_0^\Delta \theta_t^2 dt \right] \leq \mathbb{E}[\Delta] = \frac{1}{\lambda} < \infty, \quad (60)$$

and the Itô integral against θ_t is square-integrable.

We aim to characterize the HJB equation adjusted for trading at discrete event dates. We again conjecture that the value function has the form $V(W, s) = u(W)A(s)$.

Expected utility growth. We first derive an expression for $\mathbb{E} \left[\frac{u(W_\Delta) - u(W_0)}{u(W_0)} \right]$. Itô's lemma gives

$$\frac{du(W_t)}{u(W_t)} = \alpha_t dt + \zeta_t dB_t. \quad (61)$$

where we define:

$$\alpha_t := (1 - \gamma) \left[r_f + \theta_t (\mu - r_f) - \frac{1}{2} \gamma \sigma^2 \theta_t^2 \right], \quad (62)$$

$$\zeta_t := (1 - \gamma) \sigma \theta_t. \quad (63)$$

Working with the level SDE for $u(W_t)$, dividing by $u(W_0)$, and integrating over $[0, \Delta]$ gives

$$\frac{u(W_\Delta) - u(W_0)}{u(W_0)} = \int_0^\Delta \frac{u(W_t)}{u(W_0)} \alpha_t dt + \int_0^\Delta \frac{u(W_t)}{u(W_0)} \zeta_t dB_t. \quad (64)$$

Let $Z_t := u(W_t)/u(W_0)$. Then $Z_t \zeta_t$ is progressively measurable and, by admissibility, $\mathbb{E} \int_0^\tau (Z_t \zeta_t)^2 dt < \infty$ for each finite τ , so the Itô integral $\int_0^\tau Z_t \zeta_t dB_t$ is a square-integrable martingale with mean zero. With $\Delta \sim \text{Exp}(\lambda)$ independent of the Brownian path,

$$\mathbb{E} \left[\int_0^\Delta \frac{u(W_t)}{u(W_0)} \zeta_t dB_t \right] = \mathbb{E} \left[\int_0^\Delta Z_t \zeta_t dB_t \right] = \mathbb{E} \left[\mathbb{E} \left[\int_0^\Delta Z_t \zeta_t dB_t \mid \Delta \right] \right] = 0. \quad (65)$$

Then

$$\lambda \mathbb{E} \left[\frac{u(W_\Delta) - u(W_0)}{u(W_0)} \right] = \lambda \mathbb{E} \int_0^\Delta Z_t \alpha_t dt = \lambda \int_0^\infty e^{-\lambda t} \mathbb{E}[Z_t \alpha_t] dt. \quad (66)$$

We now split $\mathbb{E}[Z_t \alpha_t] = \mathbb{E}[\alpha_t] + R(t)$, where we define the remainder

$$R(t) := \mathbb{E}[(Z_t - 1) \alpha_t]. \quad (67)$$

We now evaluate the order of this remainder. Since $\theta_t \in (0, 1)$, there exists $A < \infty$ with $|\alpha_t| \leq A$. Define $m(t) := \mathbb{E}[Z_t]$. Since

$$dZ_t = Z_t \alpha_t dt + Z_t \zeta_t dB_t \quad (68)$$

and $\mathbb{E} \int_0^\tau (Z_t \zeta_t)^2 dt < \infty$, we obtain:

$$m(t) = 1 + \int_0^t \mathbb{E}[Z_r \alpha_r] dr \leq 1 + A \int_0^t m(r) dr, \quad (69)$$

so by Grönwall, $m(t) \leq e^{At}$ (see Øksendal, 2003). Consequently,

$$|R(t)| = |\mathbb{E}[(Z_t - 1)\alpha_t]| \leq A \mathbb{E}|Z_t - 1| \leq A(e^{A \cdot t} - 1). \quad (70)$$

So we obtain for $\lambda > A$:

$$\lambda \int_0^\infty e^{-\lambda t} |R(t)| dt \leq A \lambda \int_0^\infty e^{-\lambda t} (e^{A \cdot t} - 1) dt = \frac{A^2}{\lambda - A} = O\left(\frac{1}{\lambda}\right). \quad (71)$$

Combining (66) with the remainder bound yields

$$\lambda \int_0^\infty e^{-\lambda t} \mathbb{E}[Z_t \alpha_t] dt = \lambda \int_0^\infty e^{-\lambda t} \mathbb{E}[\alpha_t] dt + O(\lambda^{-1}) = \lambda \mathbb{E} \int_0^\Delta \alpha_t dt + O(\lambda^{-1}).$$

Substituting the definition of α_t and recalling that $\theta_0 = \theta_D$ is the weight set at the last event, we obtain

$$\begin{aligned} & \lambda \mathbb{E} \left[\frac{u(W_\Delta) - u(W_0)}{u(W_0)} \right] \\ &= \lambda(1 - \gamma) \mathbb{E} \left[r_f \Delta + (\mu - r_f) \int_0^\Delta \theta_t dt - \frac{1}{2} \gamma \sigma^2 \int_0^\Delta \theta_t^2 dt \mid \theta_0 = \theta_D \right] + O(\lambda^{-1}). \end{aligned} \quad (72)$$

We now evaluate the expectations of the integrals involving θ_s and θ_s^2 . To do so, we utilize Dynkin's formula (see Dynkin, 1965; Øksendal, 2003). For the Markov process (θ_t) with generator $\mathcal{L}$, we obtain for any $\varphi \in C^2([0, 1])$

$$\mathbb{E}_\theta[\varphi(\theta_t)] = \varphi(\theta) + \mathbb{E}_\theta \int_0^t \mathcal{L} \varphi(\theta_r) dr, \quad (73)$$

where the dynamics of θ given in (59) imply the infinitesimal generator

$$\mathcal{L} \varphi(x) = x(1 - x) (\mu - r_f - \sigma^2 x) \varphi'(x) + \frac{1}{2} \sigma^2 x^2 (1 - x)^2 \varphi''(x). \quad (74)$$

The Dynkin formula yields the following expansions for small deterministic t :

$$\mathbb{E}_\theta[\varphi(\theta_t)] = \varphi(\theta) + t \mathcal{L} \varphi(\theta) + O(t^2) \quad (75)$$

$$\mathbb{E}_\theta \int_0^t \varphi(\theta_r) dr = t \varphi(\theta) + \frac{1}{2} t^2 \mathcal{L} \varphi(\theta) + O(t^3) \quad (76)$$

Integrating the first expansion (75) over $s \in [0, t]$ yields the second (76). Conditioning on Δ and taking expectations yields:

$$\begin{aligned} \mathbb{E} \left[\int_0^\Delta \varphi(\theta_r) dr \right] &= \mathbb{E} [\Delta \varphi(\theta) + \frac{1}{2} \Delta^2 \mathcal{L} \varphi(\theta) + O(\Delta^3)] \\ &= \frac{\varphi(\theta)}{\lambda} + \frac{\mathcal{L} \varphi(\theta)}{\lambda^2} + O(\lambda^{-3}), \end{aligned} \quad (77)$$

where we use $\mathbb{E}[\Delta] = 1/\lambda$, $\mathbb{E}[\Delta^2] = 2/\lambda^2$. With $\varphi(x) = x$ and $\varphi(x) = x^2$ we obtain:

$$\mathcal{L}(x)(\theta) = \theta(1-\theta)(\mu - r_f - \sigma^2 \theta) \quad (78)$$

$$\mathcal{L}(x^2)(\theta) = 2\theta^2(1-\theta)(\mu - r_f - \sigma^2 \theta) + \sigma^2 \theta^2(1-\theta)^2 \quad (79)$$

and we define $b(\theta) := \mathcal{L}(x)(\theta)$. Correspondingly, we get:

$$\mathbb{E} \left[\int_0^\Delta \theta_t dt \right] = \frac{\theta}{\lambda} + \frac{b(\theta)}{\lambda^2} + O(\lambda^{-3}), \quad (80)$$

$$\mathbb{E} \left[\int_0^\Delta \theta_t^2 dt \right] = \frac{\theta^2}{\lambda} + \frac{2\theta^2(1-\theta)(\mu - r_f - \sigma^2 \theta) + \sigma^2 \theta^2(1-\theta)^2}{\lambda^2} + O(\lambda^{-3}). \quad (81)$$

Using these relations and the fact that θ_D is the event-time weight, we obtain the per-time diffusive block:

$$(1-\gamma) \left[r_f + \theta_D \cdot (\mu - r_f) - \frac{1}{2} \gamma \sigma^2 \theta_D^2 \right] + \frac{1-\gamma}{\lambda} g(\theta_D) + O(\lambda^{-1}), \quad (82)$$

where the correction polynomial relative to continuous rebalancing is

$$g(\theta_D) := (\mu - r_f) \theta_D (1 - \theta_D) ((\mu - r_f) - \sigma^2 \theta_D) - \gamma \sigma^2 \theta_D^2 (1 - \theta_D) ((\mu - r_f) - \sigma^2 \theta_D) - \frac{1}{2} \gamma \sigma^4 \theta_D^2 (1 - \theta_D)^2. \quad (83)$$

Jump block and marginal exposure to the shifter state. For a marginal exposure $d\beta$ with $s \in \{-1, 0, +1\}$, we can write:

$$\kappa(s) = e^{-\beta s} - 1 = -s d\beta + O(d\beta^2). \quad (84)$$

Using $(1+x)^{1-\gamma} = 1 + (1-\gamma)x + O(x^2)$ and independence of Δ , we obtain

$$\mathbb{E}[(1 + \theta_\Delta \kappa(s))^{1-\gamma} \mid \theta_0 = \theta_D] = 1 - (1-\gamma) \mathbb{E}[\theta_\Delta \mid \theta_0 = \theta_D] s d\beta + O(d\beta^2), \quad (85)$$

and by the Dynkin expansion,

$$\mathbb{E}[\theta_\Delta \mid \theta_0 = \theta_D] = \theta_D + \frac{b(\theta_D)}{\lambda} + O(\lambda^{-2}). \quad (86)$$

Discrete HJB and FOC. With $V(W, s) = u(W)A(s)$, the per-time HJB is

$$\begin{aligned} 0 = & -\rho A(s) + (1-\gamma)A(s) \left[r_f + \theta_D \cdot (\mu - r_f) - \frac{1}{2} \gamma \sigma^2 \theta_D^2 \right] + \frac{1-\gamma}{\lambda} A(s) g(\theta_D) \\ & + \lambda \left\{ \pi_R C(0) \mathbb{E}[(1 + \theta_\Delta \kappa(s))^{1-\gamma} \mid \theta_0 = \theta_D] + (1 - \pi_R) C(s) - A(s) \right\} \\ & + O(\lambda^{-1}) + O(\lambda d\beta^2). \end{aligned} \quad (87)$$

Differentiating w.r.t. θ_D and dividing by $(1-\gamma)A(s)$ yields the FOC:

$$\begin{aligned} 0 = & (\mu - r_f) - \gamma \sigma^2 \theta_D + \frac{g'(\theta_D)}{\lambda} - \lambda \pi_R \frac{C(0)}{A(s)} \left(1 + \frac{b'(\theta_D)}{\lambda} \right) s d\beta \\ & + O(\lambda^{-1}) + O(\lambda d\beta^2) + O(\lambda^{-1} d\beta). \end{aligned} \quad (88)$$

Sensitivity to β at $\beta = 0$. Let θ_D^* solve the FOC. Differentiate at $\beta = 0$ (so $A(s) = A(0)$):

$$f_\theta \frac{d\theta_D^*}{d\beta} \Big|_0 + f_\beta = 0, \quad (89)$$

with

$$\begin{aligned} f_\theta &= -\gamma\sigma^2 + \frac{g''(\theta_D^*)}{\lambda} + O(\lambda^{-1}), \\ f_\beta &= -\lambda \pi_R \frac{C(0)}{A(0)} \left(1 + \frac{b'(\theta_D^*)}{\lambda} \right) s + O(\lambda^{-1}). \end{aligned} \quad (90)$$

Evaluating at the optimal solution at $\beta = 0$, denoted by $\theta_{D,0}^*$, gives

$$\left. \frac{d\theta_D^*}{d\beta} \right|_{\beta=0} = -\frac{f_\beta}{f_\theta} = -\frac{\lambda \pi_R C(0)}{A(0) \gamma \sigma^2} \left(1 + \frac{b'(\theta_{D,0}^*)}{\lambda} + \frac{g''(\theta_{D,0}^*)}{\lambda \gamma \sigma^2} \right) s + O(\lambda^{-1}). \quad (91)$$

Normalizing by $\theta_{D,0}^*$ yields the state-exposure elasticity under discrete trade (for large but finite λ):

$$\begin{aligned} \eta_D(s) &= -\frac{1}{s} \left(\frac{1}{\theta_D^*} \frac{d\theta_D^*}{d\beta} \right) \Big|_{\beta=0} \\ &= \frac{\pi_R C(0)}{A(0) \gamma \sigma^2 \theta_{D,0}^*} \left(\lambda + b'(\theta_{D,0}^*) + \frac{g''(\theta_{D,0}^*)}{\gamma \sigma^2} \right) + O(\lambda^{-1}). \end{aligned} \quad (92)$$

By setting $\pi_R = 1$ we obtain the true price elasticity under discrete trade (for large but finite λ):

$$\varepsilon_D = \frac{C(0)}{A(0) \gamma \sigma^2 \theta_{D,0}^*} \left(\lambda + b'(\theta_{D,0}^*) + \frac{g''(\theta_{D,0}^*)}{\gamma \sigma^2} \right) + O(\lambda^{-1}). \quad (93)$$

Thus,

$$\frac{\hat{\varepsilon}_D}{\varepsilon_D} = \frac{\eta_D}{\varepsilon_D} \rightarrow \pi_R \quad \text{as } \lambda \rightarrow \infty. \quad (94)$$

A.3 Proof of Proposition 3

We consider a Markov process for s with three states, $\Omega = \{0, 1, 2\}$, and the Markov transition probabilities:

$$q(2|1) = \pi_B \quad (95)$$

$$q(1|1) = 1 - \pi_B \quad (96)$$

$$q(0|2) = \pi_R \quad (97)$$

$$q(2|2) = 1 - \pi_R \quad (98)$$

$$q(0|0) = 1 \quad (99)$$

All other Markov transition probabilities are zero. We consider one risky asset, $J = 1$. Unless stated otherwise, we use the same notation as in the proof of Propositions 1 and 2. The proposition considers the case of discrete trade at event dates, for the case of large λ . We retain the diffusive block and Dynkin expansions from the proof of Propositions 1 and 2:

$$(1 - \gamma) \left[r_f + \theta_D \cdot (\mu - r_f) - \frac{1}{2} \gamma \sigma^2 \theta_D^2 \right] + \frac{1 - \gamma}{\lambda} g(\theta_D) + O(\lambda^{-1}),$$

with $g(\theta)$ as previously defined and

$$\mathbb{E}[\theta_\Delta \mid \theta_0 = \theta_D] = \theta_D + \frac{b(\theta_D)}{\lambda} + O(\lambda^{-2}). \quad (100)$$

Jump block. For a small exposure β ,

$$(1 + \theta_\Delta \kappa_{s,s'})^{1-\gamma} = 1 + (1 - \gamma) \theta_\Delta \kappa_{s,s'} + O(\beta^2), \quad \kappa_{s,s'} = \beta (s' - s) + O(\beta^2).$$

Hence the per-time jump contribution in the HJB at state s is

$$\lambda \left[\sum_{s'} q(s'|s) C(s') \mathbb{E}[(1 + \theta_\Delta \kappa_{s,s'})^{1-\gamma} \mid \theta_0 = \theta_D] - A(s) \right].$$

At $s = 1$, only the transition to state $s = 2$ has a nonzero return κ and positive probability. Expanding and using (100) gives, after differentiating the HJB w.r.t. θ_D and

dividing by $(1 - \gamma)A(1)$, the first-order condition:

$$0 = (\mu - r_f) - \gamma\sigma^2\theta_D + \frac{g'(\theta_D)}{\lambda} + \frac{\lambda}{A(1)}\pi_B C(2)\kappa_{1,2}\left(1 + \frac{b'(\theta_D)}{\lambda}\right) + O(\lambda^{-1}) + O(\lambda\beta^2) + O(\lambda^{-1}\beta), \quad (101)$$

with $\kappa_{1,2} = \beta + O(\beta^2)$.

State-independence at $\beta = 0$. With a zero exposure to the shifter state, we have $\kappa_{s,s'} = 0$ for all (s, s') , and the FOC yields a constant value θ_D for all states w . Hence at $\beta = 0$, the HJB for $A(\cdot)$ also implies:

$$A(0) = A(1) = A(2), \quad C(0) = C(1) = C(2).$$

Thus, we can rewrite the FOC as follows:

$$0 = (\mu - r_f) - \gamma\sigma^2\theta_D + \frac{g'(\theta_D)}{\lambda} + \frac{\lambda}{A(0)}\pi_B C(0)\beta\left(1 + \frac{b'(\theta_D)}{\lambda}\right) + O(\lambda^{-1}) + O(\lambda\beta^2) + O(\lambda^{-1}\beta). \quad (102)$$

Let $\theta_{D,0}^* := \theta_D^*(w; \lambda, 0)$ denote the exact optimal event-time weight when $\beta = 0$.

Sensitivity at $\beta = 0$ (state $s = 1$). Define the function

$$f(\theta, \beta) := (\mu - r_f) - \gamma\sigma^2\theta + \frac{g'(\theta)}{\lambda} + \frac{\lambda}{A(0)}\pi_B C(0)\beta\left(1 + \frac{b'(\theta)}{\lambda}\right) + O(\lambda^{-1}) + O(\lambda\beta^2) + O(\lambda^{-1}\beta). \quad (103)$$

The FOC is $f(\theta_D^*(1; \lambda, \beta), \beta) = 0$. Evaluating the partial derivatives at the optimal solution for $\beta = 0$, denoted by $\theta_{D,0}^*$, yields

$$\begin{aligned} f_\theta(\theta_{D,0}^*, 0) &= -\gamma\sigma^2 + \frac{g''(\theta_{D,0}^*)}{\lambda} + O(\lambda^{-1}), \\ f_\beta(\theta_{D,0}^*, 0) &= \frac{\lambda}{A(0)}\pi_B C(0)\left(1 + \frac{b'(\theta_{D,0}^*)}{\lambda}\right) + O(\lambda^{-1}). \end{aligned} \quad (104)$$

By the implicit function theorem, we then obtain:

$$\left. \frac{d\theta_D^*(1)}{d\beta} \right|_{\beta=0} = -\frac{f_\beta}{f_\theta} = \frac{\lambda \pi_B C(0)}{A(0) \gamma \sigma^2} \left(1 + \frac{b'(\theta_{D,0}^*)}{\lambda} + \frac{g''(\theta_{D,0}^*)}{\lambda \gamma \sigma^2} \right) + O(\lambda^{-1}). \quad (105)$$

State-exposure elasticity at $s = 1$. We obtain the state-exposure elasticity in state $s = 1$:

$$\eta(1) = -\frac{1}{1} \left(\frac{1}{\theta_D^*(1)} \frac{d\theta_D^*(1)}{d\beta} \right) \Big|_{\beta=0} \quad (106)$$

$$= -\frac{\lambda \pi_B C(0)}{A(0) \gamma \sigma^2 \theta_{D,0}^*} \left(1 + \frac{b'(\theta_{D,0}^*)}{\lambda} + \frac{g''(\theta_{D,0}^*)}{\lambda \gamma \sigma^2} \right) + O(\lambda^{-1}). \quad (107)$$

We can compare this solution to the true price elasticity under discrete trade, ε_D (see characterization in the proof of Propositions 1 and 2) to obtain:

$$\frac{\hat{\varepsilon}_D(1)}{\varepsilon_D} = \frac{\eta(1)}{\varepsilon_D} \rightarrow -\pi_B \quad \text{as } \lambda \rightarrow \infty. \quad (108)$$

A.4 Expressions for Holdings Dynamics in Section 3.3

Starting from the market-clearing condition in changes

$$dm_{j,t} = -\frac{dn_{j,t}}{d\beta_j} d\beta_j \quad (109)$$

we obtain the relation

$$x_j P_{j,t} d\beta_j = P_{j,t} dm_{j,t} \cdot \left(-\frac{dn_{j,t}/n_{j,t}}{d\beta_j} \frac{n_{j,t}}{x_j} \right)^{-1}. \quad (110)$$

Next, we rewrite the state-exposure elasticity of the unit demand as a function of the portfolio share demand

$$\begin{aligned}
-\frac{dn_{j,t}/n_{j,t}}{d\beta_j} - \frac{d\left(\frac{\theta_{j,t}^* W_t}{P_{j,t}}\right)/d\beta_j}{n_{j,t}} &= -\left(\frac{d\theta_{j,t}^*}{d\beta_j} \frac{W_t}{P_{j,t}} + \frac{dW_t}{d\beta_j} \frac{\theta_{j,t}^*}{P_{j,t}} - \frac{s_t W_t \theta_{j,t}^*}{P_{j,t}}\right) \frac{1}{n_{j,t}} \\
&= -\left(\frac{1}{s_t} \frac{d\theta_{j,t}^*/\theta_{j,t}^*}{d\beta_j} n_{j,t} s_t + P_{j,t} n_{j,t} s_t \frac{\theta_{j,t}^*}{P_{j,t}} - s_t n_{j,t}\right) \frac{1}{n_{j,t}} \\
&= [\eta_{j,t} + (1 - \theta_{j,t}^*)] \cdot s_t,
\end{aligned} \tag{111}$$

where we use the relations:

$$\frac{dW}{d\beta_j} = \frac{d(\sum_{j=0}^J n_{j,t} \cdot e^{\beta_j s_t} \tilde{P}_{j,t})}{d\beta_j} = n_{j,t} e^{\beta_j s_t} \tilde{P}_{j,t} s_t = P_{j,t} n_{j,t} s_t, \tag{112}$$

$$\frac{dP_{j,t}^{-1}}{d\beta_j} = \frac{d(e^{\beta_j s_t} \tilde{P}_{j,t})^{-1}}{d\beta_j} = -(e^{\beta_j s_t} \tilde{P}_{j,t})^{-2} s_t e^{\beta_j s_t} \tilde{P}_{j,t} = -\frac{s_t}{P_{j,t}}. \tag{113}$$

Safe-asset holdings dynamics in the case of one risky asset. In the case of $J = 1$, the change in the safe-asset demand in response to a marginal state exposure $d\beta_1$ of the risky asset is:

$$dm_{0,t} = -\frac{dn_{0,t}}{d\beta_1} d\beta_1 \tag{114}$$

We can further write:

$$\begin{aligned}
-\frac{dn_{0,t}/n_{0,t}}{d\beta_1} - \frac{d\left(\frac{(1-\theta_{1,t}^*) W_t}{P_{0,t}}\right)/d\beta_1}{n_{0,t}} &= -\left(-\frac{d\theta_{1,t}^*}{d\beta_1} \frac{W_t}{P_{0,t}} + \frac{dW_t}{d\beta_1} \frac{(1-\theta_{1,t}^*)}{P_{0,t}} + 0\right) \frac{1}{n_{0,t}} \\
&= -\left(-\frac{1}{s_t} \frac{d\theta_{1,t}^*/\theta_{1,t}^*}{d\beta_1} s_t \theta_{1,t}^* \frac{W_t}{P_{1,t}} \frac{P_{1,t}}{P_{0,t}} + P_{1,t} n_{1,t} s_t \frac{(1-\theta_{1,t}^*)}{P_{0,t}}\right) \frac{1}{n_{0,t}} \\
&= [-\eta_{1,t} - (1 - \theta_{1,t}^*)] \cdot s_t \cdot \frac{P_{1,t}}{P_{0,t}} \frac{n_{1,t}}{n_{0,t}}.
\end{aligned} \tag{115}$$

Plugging this result into the relation

$$x_0 P_{0,t} d\beta_1 = P_{0,t} dm_{0,t} \cdot \left(-\frac{dn_{0,t}/n_{0,t}}{d\beta_1} \frac{n_{0,t}}{x_0}\right)^{-1} \tag{116}$$

yields

$$x_0 P_{0,t} d\beta_1 = P_{0,t} dm_{0,t} \cdot \left([-\eta_{1,t} - (1 - \theta_{1,t}^*)] \cdot s_t \cdot \frac{P_{1,t} n_{1,t} n_{0,t}}{P_{0,t} n_{0,t} x_0} \right)^{-1} \quad (117)$$

We therefore obtain the following relation for the stochastic process of incremental dollar holdings in the risk-free asset:

$$\{P_{0,\tau} dm_{0,\tau}\}_{\tau=t}^{\infty} = \left\{ x_0 P_{0,\tau} s_{\tau} d\beta_1 \cdot [-\eta_{j,\tau} - (1 - \theta_{1,\tau}^*)] \cdot \frac{P_{1,\tau} n_{1,\tau} n_{0,\tau}}{P_{0,\tau} n_{0,\tau} x_0} \right\}_{\tau=t}^{\infty}. \quad (118)$$

The incremental risk-free asset unit demand simplifies to:

$$\{dm_{0,\tau}\}_{\tau=t}^{\infty} = \left\{ d\beta_1 \cdot [-\eta_{j,\tau} - (1 - \theta_{1,\tau}^*)] \cdot \frac{P_{1,\tau}}{P_{0,\tau}} \cdot n_{1,\tau} \right\}_{\tau=t}^{\infty} = \left\{ -dm_{1,\tau} \frac{P_{1,\tau}}{P_{0,\tau}} \right\}_{\tau=t}^{\infty}. \quad (119)$$

A.5 Proof of Corollary 1

The assumptions in Corollary 1 are the same as those in Proposition 2, except that we consider continuous trade. Further, equation (25) implies the following relation for the incremental holding upon inception of a dynamic the program:

$$dm_{1,t} = s_t d\beta_1 \cdot [\eta_{1,t} + (1 - \theta_{1,t}^*)] \cdot n_{1,t}, \quad (120)$$

where $\eta_{1,t}$ is the state-exposure elasticity corresponding to the postulated price dynamics. For the resolution state process, we derived in the proof of Propositions 1 and 2 the following state-exposure elasticity in states $s \in \{-1, +1\}$:

$$\eta_C(s) = \pi_R \cdot \frac{\lambda \cdot C(0)}{(\mu - r_f) \cdot A(0)}. \quad (121)$$

Moreover, given the considered marginal exposure we can write:

$$\theta_C^*(s) = \theta_C^*(0) + \theta_1 s_t d\beta_1, \quad (122)$$

for some constant θ_1 . Plugging these results into (120) yields

$$dm_{1,t} = s_t d\beta_1 \cdot [\pi_R \cdot \frac{\lambda \cdot C(0)}{(\mu - r_f) \cdot A(0)} + (1 - (\theta^*(0) + \theta_1 s_t d\beta_1))] \cdot n_{1,t}, \quad (123)$$

$$= s_t d\beta_1 \cdot [\pi_R \cdot \frac{\lambda \cdot C(0)}{(\mu - r_f) \cdot A(0)} + (1 - \theta^*(0))] \cdot n_{1,t}. \quad (124)$$

As a result, the initial unit change in the risky asset declines linearly in the per-event resolution probability π_R .

A.6 Measuring Outsider Flows

Consider a single wedge jump from the pre-state w to the post-state w' , keeping the notation introduced in Section 3. Let $\theta_j^- = \theta_j^*(s)$ and $\theta_j^+ = \theta_j^*(s')$ be the optimal shares before and after the jump, and denote the pre-jump price by P_j^- . The price and wealth immediately after the jump are given by:

$$P_j^+ = P_j^- (1 + \kappa), \quad \kappa := e^{\beta_j(s' - s)} - 1,$$

$$W^+ = W^- \left[1 + \theta_j^- \kappa \right]$$

The unit positions of insiders, n_j , and outsiders, m_j , are given by:

$$n_j^- = \frac{\theta_j^- W^-}{P_j^-},$$

$$n_j^+ = \frac{\theta_j^+ W^+}{P_j^+} = \frac{\theta_j^+ W^-}{P_j^-} \frac{1 + \theta_j^- \kappa}{1 + \kappa}.$$

Because the outsiders clear the market in units, $\Delta m_j = -(n_j^+ - n_j^-)$, implying

$$\Delta m_j = \frac{W^-}{P_j^-} \left[\theta_j^- - \theta_j^+ \frac{1 + \theta_j^- \kappa}{1 + \kappa} \right].$$

B Data and Measurement

B.1 Predictive Regressions

The main dataset used in this analysis is the dataset "IV.dta" from the replication files of KY19. This dataset consists of a quarterly (FDATE) panel dataset on stocks (PERMNO). The sample period is 1980Q1-2017Q4. For each PERMNO/FDATE, the dataset provides information on the characteristics of that stock as well as the value of the instrument for that stock's market cap (*IVme*). The construction of the latter variable is explained in a later section. All characteristics represent signals computed at quarter-end. Accounting variables are lagged by 6 months compared to market variables. Profitability (*profit*) is the ratio of operating profits to book equity (operating profits are defined as revenue REVTS minus cost of goods sold COGS, SG&A expenses XSGA and interest expenses XINT) to book equity. Investment (*Gat*) is the annual log growth rate of book assets. The numerator in the dividend-to-book ratio (*divA_be*) represents the sum of the past 12 months of dividend payouts. Market betas (*beta*) are computed with 60-month rolling windows. This dataset has 615,789 observations.

To this baseline dataset, information on monthly stock returns are added as follows. For each PERMNO/FDATE that appears in IV.dta, three columns *retm1*, *retm2* and *retm3* are added and filled with the three monthly returns for the corresponding stock in the corresponding quarter. For instance, for PERMNO 10107 (MSFT) and FDATE 2000Q1, those three columns take on values -0.161670, -0.086845 and 0.188811 respectively. Monthly stock returns from CRSP are retrieved from common stocks (codes 10 and 11) and adjusted for potential delisting. NYSE size breakpoints at the end of each quarter are retrieved from Kenneth French's website and added to the dataset.

For a given PERMNO, quarterly observations may not be consecutive. This may be due to missing data on stock characteristics or returns for some quarters or months. While not frequent, this phenomenon affects 4,219 rows that represent time gaps of 2 quarters or more, with most occurrences pertaining to microcap stocks. KY define the universe of stocks as common stocks with nonmissing data on characteristics and return. To avoid incomplete time series, the longest sequence of quarterly observations for each PERMNO is retained. The resulting dataset has 574,541 observations.

For each PERMNO/FDATE, LNme is the log of the market capitalization of the stock, BtM is its book-to-market ratio. Momentum returns (as of the end of the quarter, i.e its last month) are computed as the compounded return of that stock over the past 3 quarters and the first two months of the considered quarter.

B.2 Elasticity Estimates

The first step is to construct the portfolio weights of institutional money managers. Data on reported 13F holdings are from Thomson Reuters' S34 dataset and start in 1980Q1. In this dataset, one row identifies a number of shares (SHARES) of a given security (CUSIP) held by a given institution (MGRNO) at a given date (FDATE, in quarters). Information on 13F filers are provided by the file "Manager.dta" retrieved from KY's replication file. Institutions in the S34 dataset that can't be matched to an institution in "Manager.dta" or for whom RDATE and FDATE do not coincide are discarded. S34 identifies positions with stock CUSIPs. The crosswalk between CUSIP and PERMNO provided by CRSP is used. Information on stock prices (PRC) and shares outstanding (SHROUT) at quarter-end as well as share codes (SHRCD) are obtained from CRSP Monthly Stock File. Stock characteristics are from the "IV.dta" file presented earlier. Positions whose share codes are not 10, 11, 12 or 18 are discarded. If a position in S34 has a value for SHARES above SHROUT, SHARES is set equal to SHROUT. If the sum of shares of a given security held by 13F filers at a given fdate exceeds SHROUT, all positions are scaled down by the corresponding ratio.

The "household sector" ($MGRNO = 0$, "HH") is then defined following KY as holding residual shares outstanding (if any) for all securities in the universe. Likewise, following KY, all positions of a given MGRNO at a given FDATE in a stock with share code 12, 18 or with missing return or characteristics are aggregated and labelled as the "outside asset" ($PERMNO = 0$). If a given MGRNO has assets under management (AUM) below 10M at any given time and or if it has no holding in the outside asset, its holdings are rebated to the HH sector. Once these modifications are made, AUMs are recomputed portfolio weights are computed. For any row, RWEIGHT is the ratio of that position's weight in the corresponding MGRNO's portfolio (at the FDATE considered) and the weight of the outside asset. Based on data made publicly available by KY for 2007Q4, it is possible to compare the proximity between

the relative portfolio weights generated by this procedure and those in their file. Over 2007Q4, the median absolute error $\frac{|rweight - rweight_{KY}|}{rweight_{KY}}$ is 0.0005.

For any given MGRNO/FDATE, rows with zero values for RWEIGHT are added for PERMNOs that have been held during any of the past 11 quarters by this MGRNO (but are not held during the quarter in consideration). This set of PERMNOs (held currently or in the past 11 quarters) is called the MGRNO's investment universe at that date. The number of stocks held in nonzero amount is labeled NHOLDING. Once the investment universe of each institution is defined, it is possible to construct $IVme_{it}(n)$ for a stock n and an institution i at time t as in KY, formula (19). It is possible to compare the generated values of IVme for the HH sector to the values retrieved from the file IV.dta. Over the sample period, the median absolute error $\frac{|IVme - IVme_{KY}|}{IVme_{KY}}$ is 0.04.

Finally, only MGRNO/FDATE pairs with NHOLDING of at least 1000 are retained for the following analysis.